Gaming, Anxiety, and Life Satisfaction: Unveiling the Hidden Patterns

Sidharth Palakode Raju

A Thesis in
The Department
of
Supply Chain and Business Technology Management

Presented in Partial Fulfilment of the Requirements
for the Degree of Master of
Business Analytics and Technology Management at
Concordia University
Montréal, Quebec, Canada

October 2024

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: Sidharth Palakode Raju

Entitled: Gaming, Anxiety, and Life Satisfaction: Unveiling the Hidden Patterns

and submitted in partial fulfillment of the requirements for the degree of

Master of Business Analytics and Technology Management

complies with the university's regulations and meets accepted standards concerning originality and quality.

Signed by the final Examining Committee:

______________________________ Chair

Dr. Danielle Morin

______________________________ Examiner

Dr. Dongliang Sheng

______________________________ Examiner

Dr. Rustam Vahidov

______________________________ Supervisor

Dr. Salim Lahmiri

Approved by ____

Chair of Department or Graduate Program Director

__________2024 ____

Dr. Anne-Marie Croteau Dean of John Molson School of Business

ABSTRACT

Gaming, Anxiety, and Life Satisfaction: Unveiling the Hidden Patterns

Sidharth Palakode Raju

This thesis explores the intricate relationship between gaming behaviors and their impact on anxiety levels and life satisfaction among gamers. Utilizing a dataset from Kaggle comprising 13,465 participants and 55 variables, the study employs both logistic and probabilistic regression analyses to examine how various demographic, behavioral, and sociocultural factors influence mental health outcomes in gamers. The regression models identify significant predictors for different anxiety and satisfaction with life classes, highlighting the roles of factors like gender, employment status, reason for playing, and gaming hours.

The findings underscore the pervasive nature of anxiety and its negative impact on life satisfaction. High levels of anxiety often overshadow positive experiences, leading to diminished well-being. The study also highlights the importance of focusing on interventions based on which factors have the most significant effect on these mental health concerns under study, suggesting that strategies to reduce anxiety and enhance life satisfaction should consider demographic differences and specific gaming behaviors. Despite the reliance on self-reported data and potential sample biases, the research provides valuable insights for developing targeted mental health interventions for the gaming community.

Acknowledgement

I would like to express my deepest gratitude to all those who supported me throughout the completion of this thesis.

First and foremost, I wish to thank my advisor, Dr Salim Lahmiri, whose expertise, understanding, and patience added considerably to my graduate experience. I would also like to thank the panel members, Dr. Danielle Morin, Dr. Dongliang Sheng, Dr. Rustam Vahidov.

I am also thankful to Dr. Suchit Ahuja for all his advice that helped me excel in the M.Sc. program. Finally, I am extremely grateful to my parents and partner for supporting me throughout my time.

Thank you all for your support and encouragement.

Table of Contents

List of Tables

List of Figures

1. Introduction

Video games have become an integral part of modern entertainment, significantly influencing culture, technology, and society. The rise of video games can be attributed to their widespread accessibility, innovative technology, and engaging content. According to an article in The Economist (2023), the video game industry has expanded to billions of players globally, demonstrating its massive reach and impact. Video games are no longer seen as a childish distraction and have transformed into a universal pastime. However, millions of people worldwide have become involved in the conversation over the impact of gaming on mental health and general well-being. Amid this discussion, an interesting field of study has emerged: the relationship between gaming and psychological aspects, including anxiety and life satisfaction.

Anxiety, characterized by excessive worry and apprehension, can significantly affect the quality of life. It is recognized as a prevalent mental health concern globally (*Anxiety Disorders*, 2023), and manifests in various forms and intensities, often influenced by an individual's environment, lifestyle, and activities. Conversely, life satisfaction represents a person's subjective assessment of their level of well-being. A vital indicator of subjective well-being, life satisfaction takes into account both an individual's emotional and cognitive reactions to their circumstances. Anxiety manifests in many forms, including social anxiety, generalized anxiety, and specific phobias, each with unique characteristics. Similarly, life satisfaction is not a single concept; it has various domains like emotional well-being, self-worth, and meaning in life.

This research paper delves into a comprehensive exploration of the intricate relationship between gaming behaviors and their impact on anxiety levels and life satisfaction. The main goal of the study will be to investigate what factors help to explain anxiety and satisfaction with life among video gamers. To achieve this, the study employs logistic and probabilistic regression to find out the significance of predictors. Offering insights into the likelihood of various outcomes based on the input data. Logistic regression assumes a logistic distribution, while the probabilistic model assumes a normal distribution. Using both models, we plan to check the consistency in the results across these different distributional assumptions: normal versus logistic. This dual approach enables a detailed examination of how different factors influence the mental health and overall well-being of gamers. The input data also span a spectrum of gaming-related variables, including but not limited to game genre, duration of gameplay, frequency of gaming sessions, social interactions within gaming communities, and reason for playing.

The global gaming industry is a multi-billion-dollar enterprise, its advancements in software development, hardware manufacturing, and digital distribution. This study carries significant business implications for the gaming, mental health, and employee well-being sectors. Companies in the gaming industry, as well as those in related sectors like mental health and wellness, can use this knowledge to develop products, services, and marketing strategies that improve player well-being and address potential mental health concerns. For example, gaming companies may design features that promote life satisfaction or reduce anxiety by integrating well-being features and setting limits for end users based on an individual's traits using the insights from this paper. Furthermore, Mental health service providers can offer targeted interventions for gamers, opening new opportunities for partnerships and innovations that cater to the mental well-being of a vast and growing global audience.

The remainder of the paper is organized as follows: Section 2 presents a comprehensive Literature Review. Section 3 will explain the objectives and contributions of this paper. Section 4 will detail the steps taken about the logistic and probabilistic regression that was performed. Section 5 introduces our dataset. Section 6 is our Results followed by Section 7 which will have the discussions and limitations. Finally, Section 8 will conclude our main findings and discuss future research directions.

2. Literature Review

The intersection of gaming, anxiety, and life satisfaction has recently attracted increasing research attention, fueled by the rapid growth of video game popularity and growing concerns about their potential psychological impact. While studies investigating the relationship between gaming and well-being exist, not much research delves into the nature of both anxiety and life satisfaction, often employing binary classifications or focusing on single aspects of well-being.

One of the earliest attempts Mehroof & Griffiths (2010), tried to examine the relationship between personality traits and online gaming addiction using students and used multiple linear regression to analyze the associations between various personality traits and online gaming addiction. The paper highlighted the importance of different personality traits in the acquisition, development, and maintenance of online gaming addiction. Liu et al. (2009) focused on using physiology-based affect recognition in intelligent tutoring systems and affective gaming. The paper presented experimental designs for affective model building and evaluating the effects of affect-based dynamic difficulty adjustment (DDA) in gaming. The results showed that the real-time prediction accuracy of the affective models is high, and the regression tree technique is efficient for effective modelling in terms of predictive accuracy and time and space cost.

The potential of commercial video games to mitigate symptoms of depression and anxiety was explored by Kowal et al. (2021). The authors acknowledged the limitations of traditional mental health treatments and the need for accessible, cost-effective interventions. The review research demonstrated that video games can improve cognitive skills and mental health outcomes up to a certain extent. The paper by Bonnaire & Baptista (2019) found that alexithymia, depression, and anxiety were significantly associated with internet gaming disorder (IGD). They also discuss the clinical implications of the findings, suggesting the use of specific psychotherapeutic techniques for individuals who use MOBA games as an emotion regulation strategy.

Chitale et al. (2022) conducted a valuable scoping review examining the potential of video games and virtual reality (VR) for assessing mental health conditions, particularly anxiety and depression. Their work not only identified promising avenues for future research but also highlighted current limitations in existing studies. Notably, the review identified three studies employing machine learning models, with support vector machines (SVMs) demonstrating the best performance. One study, in particular, achieved an impressive 86.3% accuracy in classifying anxiety using an SVM with a radial basis function kernel.

In the paper, Gosztonyi, (2023) showed that in a semi-peripheral country, the adult population plays video games in a similar proportion as in the central countries, but at the same time, a high degree of polarization can be demonstrated in the time spent gaming. Cardoso et al. (2021) investigated the link between ADHD and video game use in adolescents, noting the growing interest in problematic gaming now recognized as a distinct disorder. They identified specific game features like immortality and infinity as potential risk factors and used machine learning to analyze causal pathways, highlighting the role of stress, mental health symptoms, and hostility in IGD development.

In a study, Marques et al. (2023) explored the link between escaping into virtual gaming and mental health. Their analysis of 36 studies revealed escapism as a major motivator for playing video games and e-sports but also identified its connection to negative clinical traits and mental health concerns. The researchers categorized the findings, shedding light on the complex relationship between escapism and gaming's potential impact on public well-being.

It was Wang et al. (2017) that discovered a significant correlation between IGD and generalized anxiety disorder (GAD), revealing higher GAD prevalence among individuals with IGD, intensifying depression and anxiety symptoms. Lee et al. (2015) aimed to develop a model of MMORPG (Massive Multiplayer Online Role-Playing Game) use in the context of social anxiety. The authors used the cognitive-behavioral model of pathological internet use as a framework and examined the relationship between social anxiety, expression of the true self, social support, and levels of MMORPG use. They found that the model is invariant across two samples, indicating a good fit.

In their study, Rahman et al. (2021) employed nine distinct machine learning algorithms to assess anxiety levels in online gamers, with the Multilayer Perceptron (MLP) exhibiting exceptional accuracy when compared to Support Vector Machine (SVM), Gradient Boosting (GB) and XGBoost (XGB) displayed. Their findings underscore the potential of machine learning in comprehending the impact of online gaming behaviors on anxiety, highlighting MLP's efficacy in diagnosis. Salmani et al. (2021) apply machine learning to forecast anxiety and depression in gamers, identifying K-Nearest Neighbor (KNN) as the most accurate model, offering preventive measures for mental health concerns in gaming.

Stavropoulos et al. (2023) explore machine learning's role in mental health diagnostics, targeting disordered gaming risk reduction. Employing diverse classifiers, such as LASSO, SVM-Kernel, and K-Nearest Neighbor (KNN), they find Random Forests excelling, particularly in predicting immersion. Aggarwal et al. (2020) utilized game data and self-esteem scores from PlayerUnknown's Battlegrounds (PUBG) to predict Internet Gaming Disorder (IGD), Generalized Anxiety Disorder (GAD), and Attention Deficit Hyperactivity Disorder (ADHD). Employing machine learning techniques like logistic regression, k-nearest neighbor, naive Bayes, and decision trees, their study revealed enhanced prediction accuracy by incorporating game stats, demographics, and self-esteem as input features.

Gharpure (2022) explores how gaming factors (game type, genre, age, gender, playtime) relate to general anxiety disorder (GAD) levels. Employing basic data analytics with libraries like pandas and matplotlib, potential indicators are visually identified. Two models are proposed: a C-Support Vector Classification model using a separating hyperplane to classify the game, and a Multi-layer Perceptron classifier using LBFGS for dataset classification.

Han et al. (2021) employed machine learning on neuroimaging data to detect and profile Internet Gaming Disorder (IGD). Using a radiomics-based model, they extracted quantitative features from brain scans, achieving 73% accuracy in distinguishing IGD subjects from healthy controls. The study pinpointed specific brain region alterations linked to IGD, showcasing machine learning's potential in understanding its neurobiology.

Egami et al. (2022) investigated video gaming's impact on subjective well-being, employing regression and machine learning techniques to explore how gaming time affects individuals' well-being based on their characteristics in the Japanese population. The authors studied how satisfaction with life also improved based on extra hours of video games played, however they also discovered that prolonged gaming (>3 hours/day) decreased the psychological benefit. Pangistu & Azhari (2021) targeted game addiction detection in late adolescents, employing the Convolutional Neural Network (CNN). Analyzing brain waves during gaming, they utilized the Fast Fourier Transform for feature extraction, enabling the CNN model to achieve 86% accuracy, indicating its effectiveness in identifying game addiction through EEG signal classification.

Table 1 : Literature Review Table

Article Title	Forecasting model	Main Results
Mehroof & Griffiths (2010)	Multiple Linear Regression	Highlighted the importance of personality traits in online gaming addiction.
Liu et al. (2009)	Regression Tree Technique	High classification accuracy for recognizing anxiety (88.5%).
Kowal et al. (2021)	Review	Video games can improve cognitive skills and mental health outcomes to a certain extent.
Bonnaire & Baptista (2019)	Multiple Logistic Regressions	Alexithymia, depression, and anxiety were significantly associated with Internet Gaming Disorder (IGD).
Chitale et al. (2022)	Support Vector Machines (SVM)	SVM with radial basis function kernel achieved 86.3% accuracy in classifying anxiety.
Gosztonyi (2023)	Data Analysis	Identified polarization in gaming time in semi-peripheral countries similar to central countries.
Cardoso et al. (2021)	Machine Learning	Hostility and psychological well-being were directly linked to a subgroup of IGD symptoms while stress vulnerability and symptoms of mental disorders were indirectly involved in the causal pathways leading to IGD.

Marques et al. (2023)	Review	Escapist motivation (EM) for engaging in virtual gaming is strongly associated with negative emotional, social, and mental health outcomes
Wang et al. (2017)	Correlational Study	Found a significant correlation between IGD and General Anxiety Disorder (GAD), with higher GAD prevalence among IGD individuals.
Lee et al. (2015)	Bivariate Correlations	Individuals with higher social anxiety were found to be more likely to engage in problematic MMORPG.
Rahman et al. (2021)	Multiple Machine Learning Techniques	MLP showed the best accuracy (99%) in assessing anxiety levels in online gamers.
Salmani et al. (2021)	K-Nearest Neighbor (KNN)	KNN was identified as the most accurate model (94%) for forecasting anxiety and depression in gamers.
Stavropoulos et al. (2023)	Random Forests	Random Forests excelled in predicting immersion and disordered gaming risk (Accuracy 93.4%).
Aggarwal et al. (2020)	Multiple Machine Learning Techniques	GAD was predicted with Decision trees with an accuracy of 84.9%.
Gharpure (2022)	C-Support Vector Classification, MLP	Proposed models to classify games and datasets, and identified potential GAD indicators using data analytics. (Accuracy 88.1%)

Han et al. (2021)	Radiomics-Based Model	Achieved 73% accuracy in distinguishing IGD subjects from healthy controls using neuroimaging data.
Egami et al. (2022)	Regression and Machine Learning	Playing video games for an additional hour was found to reduce psychological distress and improve life satisfaction (possession of PlayStation improved life satisfaction by 0.23 SD).
Pangistu & Azhari (2021)	Convolutional Neural Network (CNN)	Achieved 86% accuracy in detecting game addiction through EEG signal classification.

3. Objectives of the research and Contributions

3.1 What the Literature is Missing

While there has been substantial research into the relationship between gaming and psychological outcomes, the existing literature sometimes lacks a comprehensive approach that considers both anxiety and life satisfaction in a nuanced manner. Most studies tend to focus on singular aspects of mental health or utilize binary classifications. Additionally, there exists less research that employs advanced analytical techniques, such as machine learning and probabilistic regression, to delve into the predictors of mental health outcomes in gamers. Moreover, many studies are limited by their sample sizes, whereas this thesis utilizes a robust dataset of approximately 10,000 entries, providing a more reliable basis for analysis.

3.2 Goals of the Research

The primary goal of this research is to conduct a thorough investigation into the factors that influence anxiety and life satisfaction among gamers. Specifically, this study aims to identify key predictors by determining the significant demographic, behavioral, and socio-cultural predictors of anxiety and life satisfaction among gamers. It aims to do this by utilizing advanced analytical methods to employ logistic and probabilistic regression analyses to provide a detailed examination of the relationships between various independent variables and the dependent variables of anxiety and life satisfaction. Lastly, the study aims to help provide insights that can inform the development of targeted mental health interventions and support mechanisms tailored to the gaming community.

3.3 Contributions

This research makes several significant contributions to the field of gaming and mental health. By examining both anxiety and life satisfaction in tandem, this study provides a more holistic understanding of the mental health outcomes associated with gaming. The use of logistic and probabilistic regression offers an analytical framework that enhances the accuracy and depth of the findings. The research highlights the importance of demographic factors, and gaming habits, in shaping anxiety and life satisfaction, thus contributing to a more nuanced understanding of these variables. Additionally, the findings have practical implications for mental health professionals, game developers, and community organizers, offering evidence-based recommendations for developing interventions that promote healthy gaming habits and improve overall well-being. By addressing these objectives and contributions, this research aims to provide valuable insights into the complex relationship between gaming, anxiety, and life satisfaction.

4. Methodology

The dataset under study provides valuable insights into the anxiety and satisfaction with life levels of gamers through a series of targeted questions. By keeping in mind only gamers, who are the target group, the data emphasizes the fact that several elements and experiences might contribute to mental health issues in this group of people.

The major feature that this dataset possesses is that it is constructed out of a mix of categorical, multiple-choice, and Likert scale-type questions which helps paint a much more detailed picture regarding each individual. However, most of the analytical tools are driven by the necessity of numerical input for operating the data. So, each categorical response has been systematically converted into numerical data using label encoding to address this. This process assigns a unique numerical value to each category, enabling more efficient processing and analysis of the data.

The first step after the data is label encoded is analysis using two main regression methods: logistic regression and probabilistic regression. Both logistic and probabilistic regression models are suitable for categorical Y and estimating the effect of each X on Y. Logistic regression assumes a logistic distribution, while the probabilistic model assumes a normal distribution. By using both models, you can check for consistency in the results across these different distributional assumptions: normal versus logistic. These procedures are formulated to identify patterns and relationships among the data, especially targeting gaming's influence on anxiety as well as players' life satisfaction.

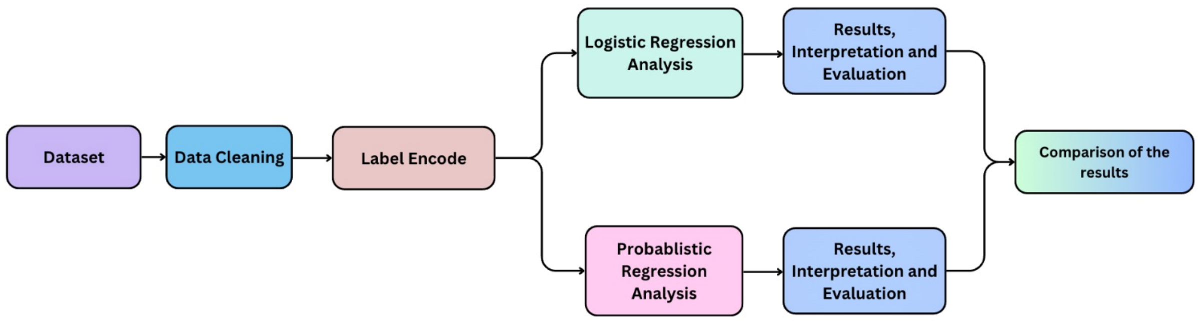

Figure 1 : Statistical Analysis flowchart

The first process is logistic regression analysis which is used to predict those possibilities. For instance, a model can be constructed that will encode whether a subject is a high or low anxiety owner. In logistic regression, the model forecasts the occurrence of the outcomes based on the input data.

At the same time, the probabilistic regression analysis which is often linear regression at this point is directed toward exploring the connection between many different independent variables that contain gaming and two primarily dependent variables anxiety and life satisfaction.

The research, with the use of data from cases of logistic and probabilistic regression, informs us about the mental health issues affecting gamers. This stance helps us spot the main predictors and measure their direct effects, all of which will contribute to the creation of targeted intervention programs and support mechanisms that can help gamers. The detailed step-by-step demonstration of this tool which starts with qualitative data and ends up with quantitative insights is the subject matter of this exercise, and it is this procedure that in effect lets the gaming, anxiety, and life satisfaction relationships reveal themselves. Figure 1 shows the flowchart of steps involved.

4.1 Regression Methodology

We have done statistical analysis using logistic and probabilistic regression to assess the gamer's anxiety levels and devise conclusions from it. Here is a brief discussion and the mathematical approach behind each algorithm in a bit of detail:

4.1.1 Logistic Regression Model

Logistic Regression (Stoltzfus et al., 2011) is a classification method used in machine learning to model the dependent variable, and a logistic (sigmoid) function is used. There are only two viable classes because the dependent variable is dichotomous. The main modelling assumption in logistic regression is that the function $a(x)$ is linear in x. In particular, in logistic regression, we have:

$$y(x) = p(C1 \mid x) = \sigma(w \top x) \tag{1}$$

where w is the weight vector for the linear model and $\top$ denotes the transpose of a matrix (vector).

The connection is nonlinear overall because of the activation function (σ), despite the linear assumption first appearing restricted. Moreover, logistic regression works quite robustly, as seen by its application in several disciplines. Since the feature vector in this model is M dimensional, there will be M parameters corresponding to $w = (w1, z2, \ldots, xM)$. In other words, the number of parameters in this model matches the number of features. It goes without saying that as features grow, so will the number of model parameters. Using basis functions or other reduction strategies is one way to lower the number of parameters.

Logistic Regression offers interpretability, facilitating the understanding of how predictor variables impact the likelihood of a specific outcome. It is particularly efficient with smaller datasets and is well-suited for constrained data availability. However, it does have limitations, including the assumption of linear relationships between predictors and the log odds of the outcome, making it less suitable for capturing complex nonlinear associations. Additionally, it can be susceptible to overfitting in cases with numerous predictors and has an assumption of predictor independence, which may not hold in practical contexts. Outliers in the data can also exert a notable influence on its performance and parameter estimates.

For a multiclass problem, logistic regression estimates the probability of each class using the following equation:

$$\log\left(\frac{P(Y=\kappa)}{P(Y=0)}\right) = \eta_{0\kappa} + \beta_{1\kappa}X_1 + \beta_{2\kappa}X_2 + \cdots + \beta_{N\kappa}X_N \qquad (2)$$

Where:

- $P(Y = \kappa)$ is the probability that the dependent variable Y belongs to class k.
- $P(Y = 0)$ is the probability that Y belongs to the reference class (often chosen as class 0).
- $\eta_{0\kappa}$ is the intercept (constant term) for class k.
- $\beta_{1\kappa}, \beta_{2\kappa}, \ldots, \beta_{N\kappa}$ are the coefficients corresponding to the predictors $X_1, X_2, \ldots, X_N$ for class k.

4.1.1.1 Logistic Regression Analysis for Anxiety Class

In this analysis, the dependent variable, Anxiety Class had its four categories: Minimal, Mild, Moderate, and Severe. To deal with this multiclass characteristic, the model incorporated the use of multinomial logistic regression which is an extension of logistic regression. It fits multiple logistic functions to relate independent variables to all the levels of the dependent variables in one step.

The independent variables in the model included a range of demographic factors (such as age and gender), behavioral aspects (like hours spent gaming and gaming motivations), and sociocultural factors (including employment status and educational level). The multinomial logistic regression model estimated the probability of each anxiety class based on these predictors, providing insights into which variables significantly influence the different levels of anxiety in gamers.

The model's implementation involved using an appropriate statistical method that supports multinomial outcomes. This allowed for the comprehensive analysis of how various factors contribute to the likelihood of gamers falling into each of the four anxiety classes. The performance and significance of the predictors were evaluated using the summary output from the fitted multinomial logistic regression model, offering a detailed understanding of the underlying factors contributing to anxiety levels within this population.

4.1.1.2 Logistic Regression Analysis for Satisfaction with Life Class

Similarly, a multinomial logistic regression model was developed to predict life satisfaction among gamers, categorized into seven classes: Slightly Dissatisfied, Satisfied, Dissatisfied, Slightly Satisfied, Neutral, Extremely Dissatisfied, and Extremely Satisfied. Multinomial logistic regression is an extension of logistic regression that allows for more than two outcome categories, making it ideal for this type of analysis.

The dependent variable in this model, Satisfaction with Life Class, included these seven distinct categories. The independent variables were the same as those used in the anxiety model, encompassing demographic factors (such as age and gender), behavioral aspects (like hours spent gaming and gaming motivations), and sociocultural factors (including employment status and educational level). The multinomial logistic regression model was used to estimate the probabilities of each life satisfaction category, providing a nuanced understanding of how various predictors influence life satisfaction among gamers.

By utilizing multinomial logistic regression, the model could effectively handle the complexity of multiple life satisfaction categories and simultaneously examine the impact of the independent variables on each category. This approach allowed for a comprehensive analysis, revealing which factors significantly contribute to the different levels of life satisfaction within the gaming community. The results from the fitted multinomial logistic regression model offered valuable insights, highlighting the key predictors of overall well-being among gamers and informing potential strategies for enhancing life satisfaction in this population.

4.1.2 Probabilistic Regression Model

In addition to logistic regression, probabilistic regression was conducted. As mentioned, prior, Logistic regression assumes a logistic distribution, while the probabilistic model assumes a normal distribution. By using both models, you can check for consistency in the results across these different distributional assumptions: normal versus logistic. This approach offers a detailed understanding of the factors affecting anxiety and life satisfaction, allowing for the analysis of the degree to which each predictor variable influences the dependent variable. By incorporating both logistic and probabilistic regression analyses, the study provides a comprehensive view of how various factors impact both anxiety and life satisfaction among gamers. Probabilistic regression analysis is a statistical approach that models the relationship between a dependent variable Y and one or more independent variables X_1, X_2,….,X_N

Linear regression models the relationship between 'p' quantitative and/or qualitative inputs $X_1, X_2, \dots, X_P$ and a quantitative output Y as a linear combination of the input variables, parameterized by some unknown parameters $\beta_0, \beta_1, \dots, \beta_p$ with noise modeled as ε. Model is expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon = \beta^T X + \varepsilon \tag{3.1}$$

Where:

$$X = (1 \quad X_1 \quad X_2 \quad \cdots \quad X_p)^T \quad \text{and} \quad \beta = (\beta_0, \quad \beta_1, \quad \cdots \quad , \beta_p)^T \tag{3.2}$$

We assume the error term ε follows a Gaussian distribution with mean zero and variance (σ^2), i.e., ($\varepsilon \sim \mathcal{N}(0, \sigma^2)$), and that ε is independent across measurements. In a maximum likelihood estimation framework, the unknown parameter ($\boldsymbol{\beta}$) is treated either as a deterministic variable or as a random variable. In both cases, (Y) is a random variable that combines the linear model ($\boldsymbol{\beta}^{\boldsymbol{T}} X$) and the noise ($\varepsilon$), leading to a Gaussian-distributed output. Thus, the distribution of Y given $\boldsymbol{\beta}$ is expressed as:

$$p(y \mid \boldsymbol{\beta}) = p_\varepsilon(y - \boldsymbol{\beta}^{\boldsymbol{T}} X) = \mathcal{N}(y \mid \boldsymbol{\beta}^{\boldsymbol{T}} X, \sigma^2) \tag{3.3}$$

We can make use of an even more compact notation based on matrices.

$$y = X\beta + E \tag{3.4}$$

The problem of learning θ from y, for which we will take the maximum likelihood approach. We factorize the data distribution

$$p(y \mid \boldsymbol{\beta}) = p(y_1, y_2, \ldots, y_N \mid \boldsymbol{\beta}) = \prod_{i=1}^{N} p(y_i \mid \boldsymbol{\beta}) = \prod_{i=1}^{N} \mathcal{N}(y_i \mid \boldsymbol{\beta}^{\boldsymbol{T}} x_i, \sigma^2) \tag{3.5}$$

With the likelihood function $L(\boldsymbol{\beta})$, the value of the data distribution evaluated at the training data y would be:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{N} \mathcal{N}(y_i \mid \boldsymbol{\beta}^{\boldsymbol{T}} x_i, \sigma^2) \tag{3.6}$$

Note that $L(\boldsymbol{\beta})$ is a function of the model parameter ($\boldsymbol{\beta}$) with the training data kept fixed. The likelihood function is thus a deterministic function of the unknown deterministic variable ($\boldsymbol{\beta}$) obtained by considering $p(y \mid \boldsymbol{\beta})$ for a fixed y. The idea in maximum likelihood is to select the value for $\boldsymbol{\beta}$ that maximizes the likelihood function, resulting in

$$\widehat{\boldsymbol{\beta}_{\mathrm{ML}}} = \arg\max_{\boldsymbol{\beta}} L(\boldsymbol{\beta}) \tag{3.7}$$

Hence, the maximum likelihood estimate $\widehat{\boldsymbol{\beta}_{\mathrm{ML}}}$ is defined as the parameter value that makes the observed outputs as likely as possible. An equivalent formulation of (3.7) is obtained by instead maximizing the logarithm of the likelihood function

$$\mathrm{l}(\boldsymbol{\beta}) = \log(L(\boldsymbol{\beta})) = \log\left(\prod_{i=1}^{N} \mathcal{N}(y_i \mid \boldsymbol{\beta}^{\boldsymbol{T}} x_i, \sigma^2)\right) \tag{3.8}$$

The resulting maximum likelihood problem is given by

$$\widehat{\boldsymbol{\beta}_{\mathrm{ML}}} = \arg\max_{\boldsymbol{\beta}} \mathrm{l}(\boldsymbol{\beta}) = \arg\min_{\boldsymbol{\beta}} \sum_{i=1}^{N} (y_i - \boldsymbol{\beta}^{\boldsymbol{T}} x_i)^2 \tag{3.9}$$

4.3 Model Evaluation

The models were evaluated using several statistical metrics, mainly:

4.3.1 P-values for Individual Coefficients

The p-value for an individual coefficient tests the null hypothesis that the coefficient is equal to zero (i.e., the predictor variable does not affect the dependent variable). A p-value less than 0.05 typically suggests that the predictor variable is statistically significant at the 5% significance level.

Mathematically, the p-value is derived from the z-score (or Wald statistic), which is calculated as:

$$z = \frac{\beta_i}{SE(\beta_i)} \tag{4}$$

Where:

- β_i is the estimated coefficient for predictor i.
- $SE(\beta_i)$ is the standard error of the estimated coefficient.

The p-value is then obtained from the standard normal distribution:

$$\text{P-value} = 2\cdot(1-\Phi(|z|)) \tag{5}$$

Where Φ\PhiΦ is the cumulative distribution function of the standard normal distribution.

A low p-value (typically less than 0.05) indicates that the null hypothesis can be rejected, suggesting that the predictor variable has a significant impact on the dependent variable.

4.3.2 Hosmer-Lemeshow Test

The Hosmer-Lemeshow test is a statistical test used to assess the goodness-of-fit for regression models. It evaluates whether the observed event rates match the expected event rates in subgroups of the model population. The test works by dividing the data into several groups, often deciles, based on their predicted probabilities. Within each group, it compares the number of observed events (e.g., actual occurrences of the outcome) to the number of expected events (predicted by the model).

Mathematically, the test computes a chi-square statistic from the observed and expected counts. This statistic measures the discrepancy between the observed and expected values. The formula for the chi-square statistic CCC is:

$$C = \sum_{j=1}^{g} \frac{(O_j - E_j)^2}{E_j(1 - \pi_j)} \tag{6}$$

Where:

- O_j is the observed number of events in group j.
- E_j is the expected number of events in group j.
- π_j is the average predicted probability for group j.

In essence, the Hosmer-Lemeshow test helps determine if a regression model is appropriate for the given data by checking if the model's predictions align well with the actual observed results across different segments of the data.

4.3.2 Wald Statistic

The Wald statistic is probably one of the most important statistics in logistic/probabilistic regression analysis for the assessment of individual predictor variables. Mathematically, it tests a null hypothesis on whether a particular regression coefficient is zero, indicating no effect of the predictor. The Wald statistic is calculated by taking the estimated coefficient (B) and dividing it by its standard error (SE), yielding a z-score:

$$W = \frac{\widehat{B}}{SE} \tag{7}$$

This z-score follows a standard normal distribution under the null hypothesis. If the z-score is sufficiently large in magnitude, the null hypothesis is rejected, suggesting that the predictor variable has a significant effect on the dependent variable. The Wald test's p-value helps in determining this significance level.

5. Dataset

In our research, we utilized a rich dataset from Kaggle that investigates the levels of anxiety and life satisfaction among online gamers. Though the dataset was posted to Kaggle, it was originally collected by a group of researchers Sauter et al. (2017) to motivate further research in the topic. The researchers collected demographic data as well as answers related to Anxiety, Life satisfaction, Social anxiety, and Narcissism. The surveys links were shared on the website reddit's gaming communities(among other sites), which is how the researchers were able to impressively obtain this large dataset. This dataset comprises of 13,465 participants and 55 variables. Among these 55 variables, in the original dataset it is important to note that each question pertaining to each health concern was a separate variable. So, for example, for Anxiety which was measured using the GAD-7 scale, we had 7 variables to determine the final anxiety score. As such 17 of these variables were of no relevance to this paper since it dealt with Narcissism and Social Anxiety. There were also 2 duplicate fields with 'Residence' and 'Birthplace' as well as the same fields in ISO3 format, so we only used the latter. We also did not consider unnecessary fields like timestamp, and sequence number. Finally, the variables 'League' and 'Highest League' were excluded from the analysis. This decision was made because different games have unique ranking systems, making these variables inconsistent and only relevant to multiplayer games, rather than to gaming in general.

As part of the cleanup process, the field showing the final total of the anxiety and satisfaction with life values were kept. Then we added 2 new fields 'Anxiety Class' and 'Satisfaction with Life Class' which showed the actual class like 'Minimal, Mild, Moderate, and Severe' based on the ranges specified by the scale's creators Spitzer et al. and Diener et al. Basic clean up like outliers were removed, e.g., answers to questions like 'Weekly hours playing video games' as 400, 8000, N/A etc. As well as removing records where answers were given as 'Unknown' or 'N/A' for fields like 'Residence', 'Degree', or 'Work'. This was only done after ensuring that only a small number of records are affected. After the clean up we had 10497 records remaining. The final leftover variables included age, gender, employment status, and educational level among others, forming the foundational background of the participants. Behavioral aspects, such as the number of hours spent gaming and the motivations behind gaming, were crucial for understanding the gaming habits and patterns that may correlate with mental health outcomes. These variables provide a holistic view of the participants' lifestyle and gaming behavior. Table 2 shows the classes for Anxiety and Life satisfaction as well as the independent variables.

	Anxiety Level	Life Satisfaction	Independent Variables
1	Minimal	Extremely Dissatisfied	Gender
2	Mild	Dissatisfied	Age
3	Moderate	Slightly Dissatisfied	Work
4	Severe	Neutral	Hours
5		Slightly Satisfied	Reference
6		Satisfied	Whyplay
7		Extremely Satisfied	Streams
8			Playstyle
9			Game
10			Platform
11			Degree
12			Residence_ISO3
13			Birthplace_ISO3

Table 2 : Anxiety & Life Satisfaction Classes, and Independent Variables

The dataset categorizes anxiety levels into Minimal, Mild, Moderate, and Severe, allowing for a detailed analysis of the prevalence and intensity of anxiety within the gaming community. Similarly, life satisfaction is categorized into Extremely Dissatisfied, Dissatisfied, Slightly Dissatisfied, Neutral, Slightly Satisfied, Satisfied, and Extremely Satisfied, providing a detailed view of the overall well-being and satisfaction levels among gamers.

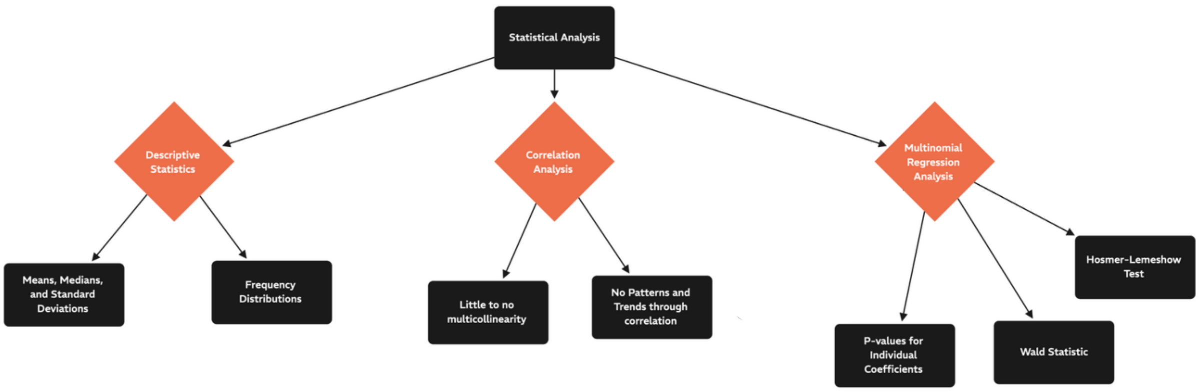

Figure 2 : Statistical Analysis Breakdown

For the statistical analysis, we first employed descriptive statistics to summarize the distribution of demographic factors and gaming habits, which revealed the profile of the participants. This step involved calculating measures such as means, medians, and standard deviations for the demographic variables, as well as frequency distributions for categorical variables. By doing this, we gained insights into the common characteristics and behaviors within the sample population. Correlation analysis was then conducted to explore the relationships between gaming habits and anxiety or life satisfaction, identifying significant patterns and trends. This analysis helped in understanding which gaming behaviors are more closely associated with higher levels of anxiety or varying degrees of life satisfaction. Figure 2 shows an overview of what statistical analysis was done with the data.

As previously mentioned, one notable aspect of the dataset is its focus on General Anxiety Disorder (GAD)(Spitzer et al, 2006), measured through seven questions related to different feelings of anxiety, each rated on four frequency scales. This detailed information allowed for precise measurement and categorization of GAD levels among the participants. We also were focused on the scoring of Satisfaction with Life (SWL)(Diener et al, 1985) questions, which was measured through using a 7-point Likert scale across five items, indicating their level of agreement. Although the dataset also included columns Single Item Narcissism Scale (SINS), and Social Phobia Inventory (SPIN), these were not utilized in our analysis as the focus was on GAD and SWL. This focus ensured that our analysis remained targeted and relevant to the primary research question regarding anxiety and satisfaction with life among gamers.

Overall, this dataset provided a valuable resource for our research, enabling a comprehensive analysis of the complex interplay of factors influencing anxiety and life satisfaction in the gaming community. The breadth and depth of the data allowed for a thorough exploration of the demographic, behavioral, and sociocultural determinants of mental health among gamers. The findings from this study contribute to the academic understanding of gaming and mental health and have practical implications for developing strategies to support the well-being of gamers. Through targeted interventions and community support, we can address the mental health challenges faced by gamers and promote a healthier, more satisfying gaming experience.

6. Results

Firstly, the Figure 3 shows a heatmap to show the multicollinearity among various factors which indicate that the majority of the independent variables that would be used in the regression model exhibit little to no multicollinearity, as evidenced by the low scores. This low level of multicollinearity suggests that these variables, including Anxiety Class, Satisfaction with life, Game, and Gender among others, are not correlated with one another and thus contribute unique information to the model. This independence among variables is ideal as it enhances the reliability and interpretability of the regression coefficients.

However, the variables Residence_ISO3 and Birthplace_ISO3 have high scores of about 0.91, indicating high multicollinearity. This suggests that these variables are somewhat correlated with each other but, that is understandable since the birthplace and residence of a person might be the same.

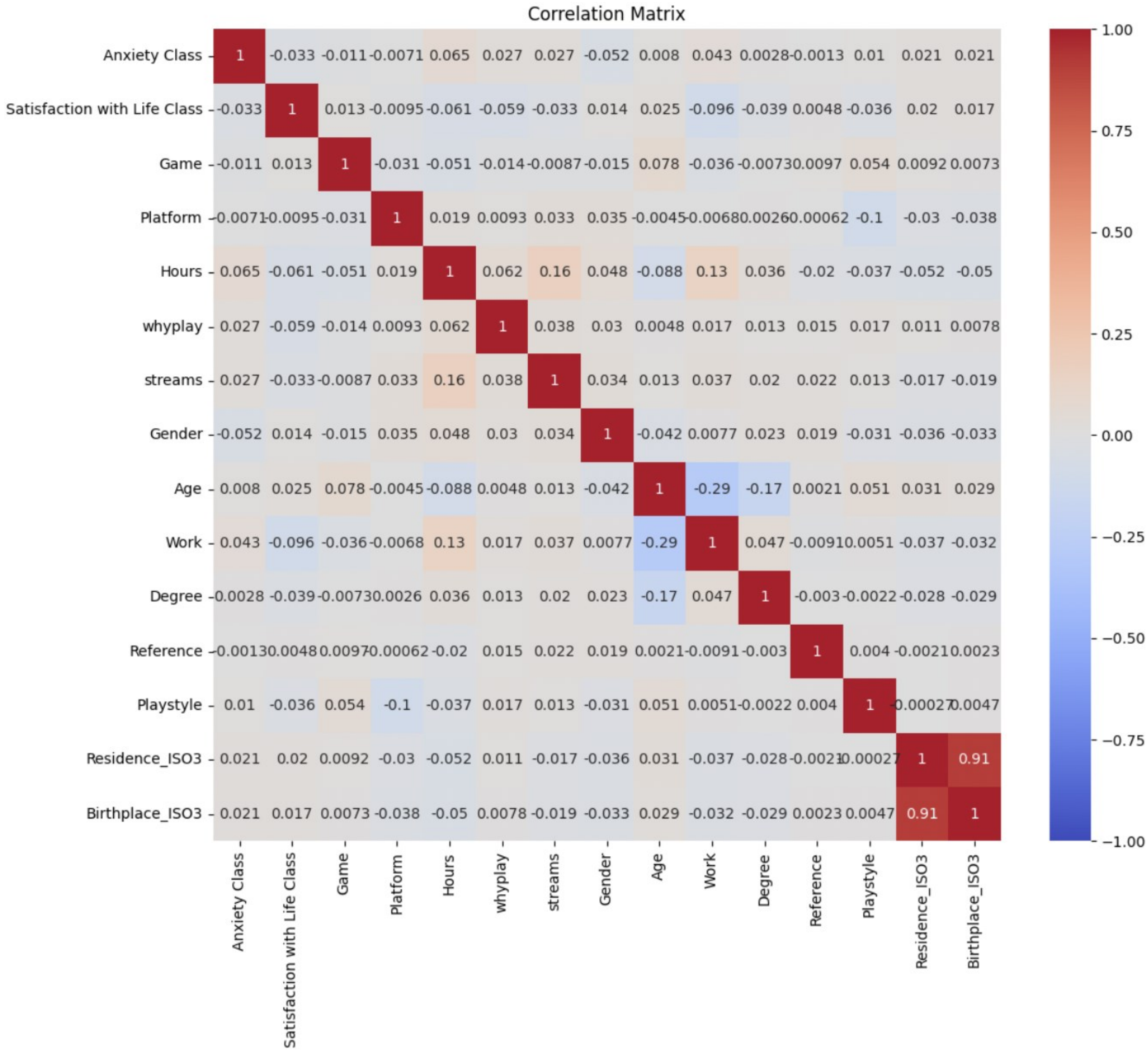

Figure 3 : Heatmap to show the multicollinearity among various factors

The logistic regression model for anxiety classes reveals significant insights into how various factors impact different anxiety classes among gamers. The dependent variable, Anxiety Class, was modelled with four categories: minimal, mild, moderate, and severe, where Mild Class serves as the reference category. The analysis was based on data from 10,497 observations. The results for each anxiety class provide a detailed understanding of the significant predictors and their implications.

Table 3 summarizes the significant predictors for each anxiety class where Mild Class serves as the reference category for logistic regression (the common variables that affect anxiety under different classes have been made bold).

Predictor	**Anxiety Class Minimal**	**Anxiety Class Moderate**	**Anxiety Class Severe**
Game	-0.0266 (p=0.157)	-0.0178 (p=0.511)	-0.0486 (p=0.160)
Platform	-0.2256 (p=0.214)	-0.7106 (p=0.002)	-0.3771 (p=0.243)
Whyplay	-0.0027 (p=0.000)	0.0024 (p=0.000)	0.0014 (p=0.0014)
Streams	-0.0094 (p=0.000)	0.0028 (p=0.364)	0.0089 (p=0.014)
Gender	0.5833 (p=0.000)	-0.4668 (p=0.000)	-0.7838 (p=0.000)
Age	0.0305 (p=0.000)	-0.0002 (p=0.984)	0.0154 (p=0.284)
Work	-0.0871 (p=0.002)	0.1166 (p=0.003)	0.2035 (p=0.000)
Hours	-0.0025 (p=0.165)	0.0086 (p=0.000)	0.0159 (p=0.000)
Degree	-0.0269 (p=0.313)	0.0144 (p=0.721)	0.0161 (p=0.768)
Reference	0.5892 (p=0.000)	-0.3600 (p=0.081)	-0.9573 (p=0.000)
Playstyle	-0.0019 (p=0.058)	0.0007 (p=0.631)	0.0005 (p=0.776)
Residence_ISO3	0.0039 (p=0.008)	0.0011 (p=0.609)	-0.0007 (p=0.811)
Birthplace_ISO3	-0.0033 (p=0.010)	-0.0010 (p=0.587)	0.0026 (p=0.306)

Table 3 : Coefficients & p-values for Anxiety Classes based on Logistic Model

In Anxiety Class minimal, gender is a significant predictor, with males being more likely to belong to this class (coef = 0.5833, $p < 0.001$). Age also plays a role, as older individuals are more likely to be in Anxiety Class minimal (coef = 0.0305, $p < 0.001$). Employment status has a negative impact, indicating that employed individuals are less likely to be in this class (coef

= -0.0871, p = 0.002). The presence of a reference significantly increases the likelihood of being in this class (coef = 0.5892, p < 0.001). Moreover, reasons for playing games (Whyplay) and watching streams both negatively affect the likelihood of being in this class (Whyplay coef = -0.0027, p < 0.001; streams coef = -0.0094, p < 0.001). Although playstyle and geographical factors such as residence and birthplace have a minor but significant impact (residence coef = 0.0039, p = 0.008; birthplace coef = -0.0033, p = 0.010), the hours spent playing do not significantly influence this class (coef = -0.0025, p = 0.165).

In Anxiety Class moderate, the number of hours spent playing is a strong positive predictor (coef = 0.0086, p < 0.001), indicating that more gaming hours increase the likelihood of being in this class. Reasons for playing games also have a small but significant positive effect (coef = 0.0024, p < 0.001). Gender shows a significant effect in the opposite direction, with males being less likely to belong to Anxiety Class moderate (coef = -0.4668, p < 0.001). Employment status has a positive impact, suggesting that employed individuals are more likely to be in this class (coef = 0.1166, p = 0.003). Although having a reference reduces the likelihood of being in Anxiety Class moderate (coef = -0.3600, p = 0.081), this effect is not statistically significant. The platform used for gaming also has a significant negative effect (coef = -0.7106, p = 0.002), while other factors like watching streams (coef = 0.0028, p = 0.364) and playstyle (coef = 0.0007, p = 0.631) do not have significant impacts.

In Anxiety Class severe, the number of hours spent playing has a substantial positive effect (coef = 0.0159, p < 0.001), suggesting that more gaming hours strongly increase the likelihood of being in this class. Watching streams also has a small but positive effect (coef = 0.0089, p = 0.014). Males are significantly less likely to belong to Anxiety Class severe (coef = -0.7838, p < 0.001), and employment status has a notable positive impact, with employed individuals more likely to experience severe anxiety (coef = 0.2035, p < 0.001). The presence of a reference greatly reduces the likelihood of being in this class (coef = -0.9573, p < 0.001). Other factors, such as the gaming platform, hours spent playing (coef = -0.0486, p = 0.160), and playstyle, show no significant effect.

Next, the Probabilistic Regression Model results provide important insights into the relationship between the predictors and anxiety levels among gamers. The R-squared value, uncentered, is 0.604, indicating that approximately 60.4% of the variance in anxiety levels can be explained by the variables included in the model (Refer table 11 in appendix). This suggests a reasonably strong explanatory power of the model. The Adjusted R-squared, also at 0.604, confirms that the model retains its explanatory power even after adjusting for the number of predictors, which helps to account for the potential overfitting.

Table 4 summarizes the significant predictors for each anxiety class where Mild Class serves as the reference category for probabilistic regression (the common variables that affect anxiety under different classes have been made bold).

Predictor	**Anxiety Class Minimal**	**Anxiety Class Moderate**	**Anxiety Class Severe**
Game	-0.0264 (p=0.159)	-0.0177 (p=0.515)	-0.0480 (p=0.165)
Platform	0.2092 (p=0.248)	-0.6877 (p=0.003)	-0.3517 (p=0.277)
Whyplay	-0.0027 (p=0.000)	0.0024 (p=0.003)	0.0014 (p=0.181)
Streams	-0.0094 (p=0.000)	0.0028 (p=0.363)	0.0089 (p=0.014)
Gender	0.5847 (p=0.000)	-0.4665 (p=0.000)	-0.7818 (p=0.000)
Age	0.0306 (p=0.000)	-0.0002 (p=0.985)	0.0158 (p=0.273)
Work	-0.0870 (p=0.002)	0.1166 (p=0.003)	0.2042 (p=0.000)
Hours	-0.0025 (p=0.165)	0.0085 (p=0.000)	0.0159 (p=0.000)
Degree	-0.0268 (p=0.315)	0.0146 (p=0.719)	0.0167 (p=0.761)
Reference	0.5770 (p=0.000)	-0.3736 (p=0.070)	-0.9839 (p=0.000)
Playstyle	-0.0019 (p=0.061)	0.0007 (p=0.622)	0.0006 (p=0.759)
Residence_ISO3	0.0039 (p=0.008)	0.0011 (p=0.607)	-0.0007 (p=0.812)
Birthplace_ISO3	-0.0033 (p=0.010)	-0.0010 (p=0.587)	0.0026 (p=0.305)

Table 4 : Coefficients & p-values results for Anxiety Classes based on Probabilistic Model

Concerning the results in table 4 we can see that the probabilistic regression results highlight several significant predictors of anxiety across minimal, moderate, and severe classes. Gender plays a key role, with a positive association with minimal anxiety (coef = 0.5847, $p < 0.001$) and negative associations with moderate (coef = -0.4665, $p < 0.001$) and severe anxiety (coef = -0.7818, $p < 0.001$), suggesting a protective effect as anxiety severity increases. Work also consistently predicts anxiety, with employment status reducing the likelihood of minimal anxiety (coef = -0.0870, $p = 0.002$) but significantly increasing both moderate (coef = 0.1166, $p = 0.003$) and severe anxiety (coef = 0.2042, $p < 0.001$). Additionally, Whyplay is a significant predictor, where the reasons for playing games slightly reduce the likelihood of minimal anxiety (coef = -0.0027, $p < 0.001$) but increase moderate anxiety (coef = 0.0024, $p = 0.003$).

The Platform used has a strong negative relationship with moderate anxiety (coef = -0.6877, $p < 0.001$), indicating that certain platforms may offer a buffer against moderate anxiety.

Furthermore, Streams significantly decrease minimal anxiety (coef = -0.0094, $p < 0.001$) while increasing severe anxiety (coef = 0.0089, $p = 0.014$), suggesting that more streaming might either alleviate or exacerbate anxiety depending on its intensity. Age shows a small but significant positive effect on minimal anxiety (coef = 0.0306, $p < 0.001$), while Reference has a strong influence, positively predicting minimal anxiety (coef = 0.5770, $p < 0.001$) and negatively predicting severe anxiety (coef = -0.9839, $p < 0.001$). Finally, both Residence_ISO3 (coef = 0.0039, $p = 0.008$) and Birthplace_ISO3 (coef = -0.0033, $p = 0.010$) are significant in predicting minimal anxiety, with residence slightly increasing and birthplace decreasing the likelihood.

Additionally, for the probabilistic regression for anxiety, the F-statistic for the model is 1232, with a p-value less than 0.0001 (Refer to appendix table 11). This highly significant p-value demonstrates that the overall model is statistically significant, implying that the predictors jointly have a substantial impact on the dependent variable, which in this case is the anxiety levels.

The analysis highlights gender differences in anxiety classifications, with males more likely to be in Anxiety Class minimal but less likely to be in Anxiety Classes Moderate and Severe. This suggests different coping mechanisms or responses to gaming environments between genders. Employment status influences anxiety classes differently, decreasing the likelihood of being in Anxiety Class minimal but increasing the likelihood for Classes Moderate and Severe, which may reflect the stress of balancing work and gaming. Increased hours of gameplay are associated with higher anxiety classes (Moderate and Severe), indicating a link between excessive gaming and anxiety. The presence of a reference shows a complex relationship, increasing the likelihood of being in Anxiety Class minimal but decreasing it for Classes Moderate and Severe. The reasons for playing games and certain playstyles also impact anxiety classes, suggesting the need for interventions that promote healthy gaming habits.

The logistic regression model for Satisfaction with Life Class offers significant insights into how various factors influence life satisfaction among gamers. The dependent variable, Satisfaction with Life Class, was categorized into seven classes, ranging from least to most satisfied, with Class Neutral serving as the reference category. The analysis was conducted on data from 10,497 observations. The results for each satisfaction class provide a better understanding of the predictors and their implications. The details are present in table 5.

Table 5 summarizes the significant predictors for each satisfaction with life class where the Neutral Class serves as the reference category for logistic regression. (the common variables that affect satisfaction under different classes have been made bold).

Predictor	**Slightly dissatisfied**	**Dissatisfied**	**Extremely dissatisfied**	**Slightly satisfied**	**Satisfied**	**Extremely satisfied**
Game	0.0352 (p=0.371)	0.0071 (p=0.859)	-0.0024 (p=0.956)	0.0631 (p=0.112)	0.0598 (p=0.139)	0.0675 (p=0.165)
Platform	-0.8509 (p=0.054)	-0.5481 (p=0.226)	-0.9014 (p=0.057)	-0.7031 (p=0.114)	-0.7883 (p=0.078)	-1.0098 (p=0.040)
Whyplay	0.0006 (p=0.592)	0.0012 (p=0.310)	0.0023 (p=0.073)	-0.0014 (p=0.231)	-0.0028 (p=0.014)	-0.0026 (p=0.052)
Streams	0.0085 (p=0.114)	0.0108 (p=0.046)	0.0187 (p=0.001)	0.0006 (p=0.906)	0.0007 (p=0.904)	0.0035 (p=0.590)
Gender	0.1235 (p=0.545)	0.0339 (p=0.870)	-0.1129 (p=0.620)	0.3107 (p=0.131)	0.5435 (p=0.011)	0.1479 (p=0.543)
Age	0.0451 (p=0.011)	0.0571 (p=0.001)	0.0836 (p=0.000)	0.0197 (p=0.268)	0.0250 (p=0.165)	0.0675 (p=0.001)
Work	0.2024 (p=0.002)	0.3856 (p=0.000)	0.5961 (p=0.000)	0.0721 (p=0.284)	-0.0807 (p=0.243)	-0.1232 (p=0.131)
Hours	0.0017 (p=0.665)	0.0062 (p=0.121)	0.0178 (p=0.000)	-0.0020 (p=0.620)	-0.0095 (p=0.022)	-0.0025 (p=0.610)
Degree	0.0905 (p=0.127)	0.0291 (p=0.631)	0.0832 (p=0.218)	-0.0418 (p=0.480)	-0.0195 (p=0.744)	0.0670 (p=0.330)
Reference	0.3696 (p=0.274)	-0.1643 (p=0.631)	-1.2667 (p=0.000)	1.1003 (p=0.001)	1.1770 (p=0.001)	0.3781 (p=0.339)
Playstyle	-0.0017 (p=0.411)	-0.0007 (p=0.742)	0.0017 (p=0.450)	-0.0054 (p=0.013)	-0.0038 (p=0.078)	-0.0065 (p=0.016)
Residence_ISO3	0.0004 (p=0.899)	0.0025 (p=0.449)	0.0009 (p=0.810)	0.0005 (p=0.869)	0.0051 (p=0.117)	0.0007 (p=0.845)
Birthplace_ISO3	-0.0010 (p=0.720)	-0.0025 (p=0.386)	-0.0001 (p=0.970)	-0.0001 (p=0.970)	-0.0045 (p=0.112)	0.0010 (p=0.768)

Table 5 : Coefficients & p-values results for Satisfaction with Life based on Logistic Model

In Satisfaction with Life Class Slightly Dissatisfied, the significant predictors include age (coef = 0.0451, $p = 0.011$) and employment status (Work coef = 0.2024, $p = 0.002$). This suggests that older individuals and those employed are more likely to be slightly dissatisfied, while platform choice negatively impacts life satisfaction in this class. However, hours spent playing games (Hours coef = 0.0017, $p = 0.665$) and having a reference (coef = 0.3696, $p = 0.274$) do not show significant effects in this class.

In Satisfaction with Life Class Dissatisfied, age (coef = 0.0571, $p = 0.001$), employment status (coef = 0.3856, $p < 0.001$), and watching streams (coef = 0.0108, $p = 0.046$) significantly predict dissatisfaction. While hours spent playing games show no significant impact (coef = 0.0062, $p = 0.121$), reasons for playing games (Whyplay coef = 0.0012, $p = 0.310$) are not strong predictors either.

In Satisfaction with Life Class Extremely Dissatisfied, hours spent playing games (Hours coef = 0.0178, $p < 0.001$) and watching streams (coef = 0.0187, $p = 0.001$) significantly predict dissatisfaction, showing that more time spent playing or watching streams is associated with greater dissatisfaction. Age (coef = 0.0836, $p < 0.001$) and employment status (coef = 0.5961, $p < 0.001$) also contribute to dissatisfaction in this class, while having a reference (coef = -1.2667, $p < 0.001$) strongly reduces the likelihood of being extremely dissatisfied.

In Satisfaction with Life Class Slightly Satisfied, watching streams (coef = 0.0006, $p = 0.906$), hours spent playing games (coef = -0.0020, $p = 0.620$), and reasons for playing games (coef = -0.0014, $p = 0.231$) do not significantly predict life satisfaction. However, having a reference (coef = 1.1003, $p = 0.001$) and playstyle (coef = -0.0054, $p = 0.013$) have notable effects, indicating that references positively affect satisfaction, while playstyle negatively influences it.

In Satisfaction with Life Class Satisfied, hours spent playing games have a small negative impact (coef = -0.0095, $p = 0.022$), while employment status shows no significant effect (coef = -0.0807, $p = 0.243$). Additionally, geographical factors (Residence_ISO3 coef = 0.0051, $p = 0.117$; Birthplace_ISO3 coef = -0.0045, $p = 0.112$) and playstyle (coef = -0.0038, $p = 0.078$) show minor yet non-significant effects on satisfaction in this class.

In Satisfaction with Life Class Extremely Satisfied, hours spent playing games (coef = -0.0025, $p = 0.610$) and watching streams (coef = 0.0035, $p = 0.590$) do not significantly affect life satisfaction. Moreover, having a reference has little to no significance (coef = 0.3781, p =

0.339), and playstyle negatively influences it (coef = -0.0065, p = 0.016). Age (coef = 0.0675, p = 0.001) remains a significant predictor, with older individuals being more likely to feel extremely satisfied with life.

Table 6 summarizes the significant predictors for each satisfaction with life class where the Neutral Class serves as the reference category for probabilistic regression. (the common variables that affect satisfaction under different classes have been made bold).

Predictor	**Slightly Dissatisfied**	**Dissatisfied**	**Extremely Dissatisfied**	**Slightly Satisfied**	**Satisfied**	**Extremely Satisfied**
Game	0.0354 (p=0.369)	0.0072 (p=0.855)	-0.0023 (p=0.958)	0.0632 (p=0.111)	0.0599 (p=0.139)	0.0677 (p=0.164)
Platform	-0.8496 (p=0.054)	-0.5483 (p=0.226)	-0.9015 (p=0.057)	-0.7044 (p=0.113)	-0.7873 (p=0.078)	-1.0109 (p=0.040)
Whyplay	0.0006 (p=0.588)	0.0012 (p=0.307)	0.0023 (p=0.073)	-0.0013 (p=0.233)	-0.0028 (p=0.014)	-0.0026 (p=0.052)
Streams	0.0085 (p=0.114)	0.0108 (p=0.046)	0.0187 (p=0.001)	0.0006 (p=0.905)	0.0007 (p=0.904)	0.0035 (p=0.590)
Gender	0.1232 (p=0.546)	0.0338 (p=0.870)	-0.1140 (p=0.616)	0.3101 (p=0.132)	0.5417 (p=0.011)	0.1493 (p=0.539)
Age	0.0451 (p=0.011)	0.0571 (p=0.001)	0.0836 (p=0.000)	0.0197 (p=0.268)	0.0249 (p=0.165)	0.0675 (p=0.001)
Work	0.2022 (p=0.002)	0.3854 (p=0.000)	0.5958 (p=0.000)	0.0719 (p=0.285)	-0.0810 (p=0.241)	-0.1234 (p=0.130)
Hours	0.0017 (p=0.664)	0.0062 (p=0.120)	0.0178 (p=0.000)	-0.0020 (p=0.621)	-0.0095 (p=0.022)	-0.0025 (p=0.611)
Degree	0.0900 (p=0.130)	0.0286 (p=0.637)	0.0825 (p=0.222)	-0.0423 (p=0.474)	-0.0201 (p=0.737)	0.0663 (p=0.335)
Reference	0.3674 (p=0.277)	-0.1661 (p=0.628)	-1.2667 (p=0.000)	1.1005 (p=0.001)	1.1776 (p=0.001)	0.3768 (p=0.340)
Playstyle	-0.0017 (p=0.413)	-0.0007 (p=0.744)	0.0018 (p=0.448)	-0.0054 (p=0.013)	-0.0038 (p=0.078)	-0.0065 (p=0.016)
Residence_ISO3	0.0004 (p=0.899)	0.0025 (p=0.449)	0.0009 (p=0.810)	0.0005 (p=0.869)	0.0051 (p=0.117)	0.0007 (p=0.845)
Birthplace_ISO3	-0.0010 (p=0.720)	-0.0025 (p=0.387)	-0.0001 (p=0.983)	-0.0001 (p=0.970)	-0.0045 (p=0.112)	0.0010 (p=0.768)

Table 6 : Coefficients & p-values results for Satisfaction with Life based on Probabilistic Model

Finally with respect to probabilistic regression results in Table 6. We can see that Work emerges as a critical factor, with employed individuals showing a significantly higher likelihood of being extremely dissatisfied (coef = 0.5958, p < 0.001), slightly dissatisfied (coef

= 0.2022, $p = 0.002$), and dissatisfied (coef = 0.3854, $p < 0.001$), indicating that employment status has a strong positive impact on dissatisfaction. Conversely, Work is associated with a decrease in satisfaction among the satisfied class (coef = -0.0810, $p = 0.241$), although this effect is not statistically significant.

Gender shows varied effects, with a slight but significant positive impact on being satisfied (coef = 0.5417, $p = 0.011$) and no significant effects in other satisfaction categories. Age is consistently positive across several classes, significantly increasing the likelihood of being slightly dissatisfied (coef = 0.0451, $p = 0.011$), dissatisfied (coef = 0.0571, $p = 0.001$), and extremely dissatisfied (coef = 0.0836, $p < 0.001$).

Reference has a strong positive association with being satisfied (coef = 1.1776, $p = 0.001$) but a negative association with extreme dissatisfaction (coef = -1.2667, $p < 0.001$), indicating that references may serve as a protective factor against extreme dissatisfaction and promote higher satisfaction. Platform also plays a significant role, where its negative coefficients in the dissatisfied (coef = -0.5483, $p = 0.226$) and satisfied classes (coef = -0.7873, $p = 0.078$) suggest a platform effect on dissatisfaction.

Streams show a mixed influence, increasing the likelihood of extreme dissatisfaction (coef = 0.0187, $p = 0.001$) while not significantly impacting other satisfaction levels. Playstyle slightly reduces the likelihood of being satisfied (coef = -0.0038, $p = 0.078$) and significantly decreases extreme satisfaction (coef = -0.0065, $p = 0.016$), indicating that certain playstyles might be less good for high satisfaction.

The results from the Hosmer-Lemeshow test reveal in the case of the probabilistic model for the anxiety class, the test produced a statistic of 1278.31 while in the satisfaction with life case, it was 1996.74. Low p-values indicate that the discrepancies between the observed and expected event rates are highly significant, suggesting that both models may not fit the data as well. However, this is understandable since Hosmer results are based on checking the fit of the model with all predictors considered in the model. The results would improve greatly if we removed the non-significant predictors. We have still retained the Hosmer results to enrich the results more technically.

For each model (Table 3 to 6) we also found the Wald test results to reveal key insights into the predictors for Anxiety Class and Satisfaction with Life Class. The individual Wald values showed the significant predictors just as we had seen with the p values and their coefficients.

High Wald statistic values correspond to the predictor’s significance. (Refer to appendix for detailed tables with individual values tables 29 - 33).

In conclusion, both logistic and probabilistic regression models highlight similar key predictors of anxiety and life satisfaction among gamers, such as gender, employment, hours of gameplay, Whyplay, and reference. While the models largely agree, with minor differences in coefficient magnitudes, there are occasional discrepancies—like Whyplay being significant in the logistic model but not in the probabilistic one. Overall, their consistency enhances the reliability of the findings, providing useful insights for mental health interventions in the gaming community.

7. Discussions

The primary goal of this research is to conduct a thorough investigation into the factors that influence anxiety and life satisfaction among gamers. The research provides significant insights into the intricate relationship between anxiety and satisfaction with life, emphasizing the profound impact these have on overall well-being. Anxiety and life satisfaction are critical dimensions of mental health, influencing various aspects of an individual's personal and professional life. Understanding the dynamics between these variables is crucial for developing effective interventions aimed at improving mental health and enhancing quality of life.

7.1 Summary of main findings

Anxiety, a common mental health issue, can severely impair an individual's ability to function effectively in daily life. It is associated with a range of negative outcomes, including decreased productivity, strained relationships, and poor physical health. The findings of this research highlight the pervasive nature of anxiety. High levels of anxiety can overshadow positive experiences, leading to a diminished sense of well-being and overall life satisfaction. Life satisfaction, on the other hand, is a key indicator of positive mental health and overall well-being. It reflects an individual's overall assessment of their quality of life based on their criteria. The research's findings reaffirm the importance of life satisfaction as a crucial component of mental health, highlighting the inverse relationship between anxiety and life satisfaction. This relationship suggests that efforts to enhance life satisfaction must also address underlying anxiety issues to be effective as many of the same predictors are significant in both cases of anxiety and satisfaction with life.

Demographic factors play a significant role in shaping the levels of anxiety and life satisfaction experienced by individuals. Age, for instance, has been identified as a significant factor, with older individuals generally reporting higher life satisfaction and lower anxiety levels. This may be attributed to the accumulation of life experiences, better coping mechanisms, and a more stable socio-economic status typically associated with older age. This finding suggests that interventions to reduce anxiety and enhance life satisfaction may need to be tailored differently for various age groups to be effective.

Both logistic and probabilistic regression models provide a comprehensive view of the predictors influencing anxiety and satisfaction with life among gamers. They are largely consistent in identifying key predictors like gender, employment, hours of gameplay, Whyplay, and reference. For the most part, the predictors that have shown up as significant in logistic analysis have ended up showing significance in the case of probabilistic in comparing with anxiety and satisfaction with life. However, the probabilistic model offers slightly different coefficient magnitudes. In some rare cases predictors like 'Whyplay' can be seen as a significant predictor for anxiety according to the logistic model but not concerning the probabilistic. In the end, the consistency across models strengthens the reliability of these findings, offering valuable insights for mental health interventions tailored to the gaming community.

Lastly, in this study, while nominal logistic regression could have been used as an alternative approach, it is expected that the results would mirror those obtained through standard logistic regression. This is due to the categorical nature of the outcome variables, where the distinction between different classes is unlikely to affect the overall pattern of predictors identified. Therefore, standard logistic regression remains a robust method for interpreting the data.

7.2 Comparison with previous studies

Some curious resemblances were discovered in our research. Our research revealed that anxiety and life satisfaction are highly related. Predictors that cause anxiety to go up are the same predictors that cause the level of satisfaction with life to drop down. This finding is similar with those of Mehroof & Griffiths (2010) and Liu et al. (2009), though they linked gaming habits and anxiety with traits like aggression, and Neuroticism. Moreover, they found out that there is a detrimental effect of anxiety on overall well-being. Additionally, we noted that some demographic factors such as age significantly influence levels of anxiety and life satisfaction. Generally, older people report greater life satisfaction but lower levels of tension. This agrees with what Cardoso et al.'s (2021) and Marques et al.'s (2023) observed in their studies which mainly focused on understanding demographic indicators for gaming-related psychological effects and anxiety disorders.

However, noticeable differences distinguish our study from prior work. One large difference is that our study took a more general approach to understanding the relationship between variables of anxiety and life satisfaction across a wide demographic, whereas many previous studies target the exact impact of gaming on mental health. For instance, studies conducted by Kowal et al. 2021, Chitale et al. 2022, and Aggarwal et al. 2020 examined gaming behaviors while being more specifically oriented towards investigating how such behavior has an effect on anxiety and other mental health issues like depression. Within this framework, they identified certain stressors and coping strategies that appeared to be unique to the gaming community. Our approach has relied on self-reported measures, which are thus subject to bias but differs from other studies in its range of methodologies—for instance, physiological measures, neuroimaging, and machine learning techniques. In addition, demographic characteristics in our study may be a limitation to generalizability, while studies like Gosztonyi, 2023, and Egami et al., 2022, concerned specific populations that provide very relevant insights but are not generally applicable.

7.3 Limits of the study

With respect to the limitations of the paper, the reliance on self-reported measures is one such limitation. While self-reports are a common method in psychological research, they are susceptible to biases such as social desirability and recall bias. Participants might underreport their anxiety levels or overestimate their life satisfaction due to a desire to present themselves in a favorable light. Incorporating other assessment methods, such as clinical interviews or physiological measures, could provide more objective and reliable data. Another potential limitation could be that during data collection, the researchers had posted the survey in particular subreddit pages and websites (As shown in the reference column of the dataset). Especially Reddit pages for large games (eg. league of legends) where they believed the most people would potentially fill out the survey and as such this may mean that the dataset may not be as generalizable. Moreover, the study sample's demographic characteristics may also limit the generalizability of the findings. Since the residence of people who answered the survey was concentrated on 3 countries, USA, Germany, and Great Britain, which accounted for about 7000 entries. As such, if the sample is not representative of the broader population, the results may not accurately reflect the experiences of all demographic groups.

7.4 Implications of the study and future research directions

The findings suggest the importance of preventive measures in mental health. By identifying individuals at risk of high anxiety and low life satisfaction, early interventions can be implemented to prevent the escalation of mental health issues. Schools, workplaces, and community organizations can play a vital role in providing resources and support for mental health and promoting a culture of well-being and resilience.

The findings of this study have significant business and organizational implications, particularly for industries related to gaming, mental health, and employee well-being. Given the negative impact of anxiety on life satisfaction and its potential to reduce productivity, organizations may need to implement mental health support systems within the workplace. This could involve providing access to counseling services, promoting stress management programs, or creating a more balanced work-life structure, especially in industries that involve extensive gaming or technology use based on a person's traits and habits.

Moreover, businesses that cater to gamers, such as gaming platforms and developers, could take into consideration the mental health of their user base by promoting healthier gaming habits, setting time limits, or integrating well-being features into their products. Specifically based on our results, understanding gender-based differences and the role of employment status in anxiety and life satisfaction can also help tailor workplace interventions, ensuring that employees across different demographics receive the support they need.

Future research should strive for more diverse and representative samples to ensure the findings are applicable across different populations and cultural contexts. Moreover, the study may not have accounted for all potential confounding variables. Factors such as physical health, social support, and major life events can significantly influence both anxiety and life satisfaction. Failure to control these variables may result in an incomplete understanding of the relationship between anxiety and life satisfaction. Future studies should include a broader range of variables to provide a more nuanced analysis.

In future research, exploring interaction effects between predictive variables also presents a valuable direction, particularly in the context of anxiety and life satisfaction among gamers. For example, the interaction between age and work status could influence the impact of gaming hours on mental health outcomes. Younger gamers who work part-time might experience different levels of anxiety or satisfaction compared to older gamers who work full-time, even if they engage in the same amount of gaming. Investigating these interactions can provide a more detailed understanding of how age and work dynamics shape the effects of gaming on well-being.

8. Conclusions

The complex relationship between anxiety and life satisfaction has much to say about the general condition of individuals. The findings point clearly to the principal role these psychological structures take in influencing various dimensions of the personal and professional life of a person. Through the research on the effects of anxiety and life satisfaction, valuable insight gained may be used to develop mental health interventions to effectively improve quality of life. Anxiety is a common mental health disorder that causes serious impairment in daily functioning, resulting in reduced productivity at work, impaired relationships, and poor physical health.

The primary goal of this research was to conduct a thorough investigation into the factors that influence anxiety and life satisfaction among gamers. A high level of anxiety might mask positive experiences, leading to a reduced sense of well-being and life satisfaction. This therefore calls for the need to address anxiety to enhance life satisfaction effectively.

The regression models for anxiety classes returned that several predictor variables influenced different levels of anxiety for gamers. In this case, gender was a critical predictor whereby males are more likely to belong to the minimal anxiety class and less likely to be in both moderate and severe anxiety classes. This might imply that, probably, there are gender-based ways of coping or reacting to the gaming environment. That also means employed people are less likely to drop into the class where there is minimal anxiety. In such a case, the result can be viewed as one reflecting the stress of keeping a job while gaming. The amount of time spent gaming is also a strong predictor of higher classes in anxiety, especially the moderate and heavy classes. This goes on to prove that excessive gaming is linked with increased anxiety.

Life satisfaction is an important indicator of positive mental health and overall well-being. It represents an individual's general judgment of their quality of life based on their standards. This study highlights the essential role of life satisfaction in mental health and emphasizes the negative correlation between anxiety and life satisfaction. This would point to a relationship such that efforts at enhancing life satisfaction, were they not to address the underlying issues of anxiety, would prove ineffective.

According to the regression models, predictors for satisfaction in gamers were time spent gaming, employment status, and age. That means excessive gaming hours and being employed are linked to weak life satisfaction. Therefore, interventions in fighting unhealthy gaming habits, as well as supportive environments for life satisfaction, need to be pursued.

The findings of this study have important business implications, especially for industries in gaming, mental health, and employee well-being. Organizations may need to implement mental health support systems, such as counselling services and stress management programs, to mitigate the negative effects of anxiety on productivity and life satisfaction. Gaming companies can promote healthier gaming habits by integrating well-being features and setting limits.

However, the study's limitations, including a lack of diversity in the sample and unaccounted variables like physical health and social support, suggest future research should explore a broader range of factors to deepen understanding.

In conclusion, this research highlights the complex relationship between anxiety and life satisfaction, offering valuable insights for both mental health interventions and business practices.

9. Appendix

Table 7 : Relevant summary statistics for Logistic Regression Anxiety Class

Logistic Regression for Anxiety Class (Multiclass):

MNLogit Regression Results

Dep. Variable:	Anxiety Class	No. Observations:	10497
Model:	MNLogit	Df Residuals:	10458
Method:	MLE	Df Model:	36
Date:	Tue, 09 Jul 2024	Pseudo R-squ.:	0.01910
Time:	11:25:06	Log-Likelihood:	-11262.
converged:	True	LL-Null:	-11481.
Covariance Type:	nonrobust	LLR p-value:	1.084e-70

Table 8 : Statistics for Logistic Regression Anxiety Class Minimal

Anxiety Class=1	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0266	0.019	-1.415	0.157	-0.063	0.010
Platform	-0.2256	0.182	-1.241	0.214	-0.582	0.131
Hours	-0.0025	0.002	-1.390	0.165	-0.006	0.001
whyplay	-0.0027	0.001	-5.291	0.000	-0.004	-0.002
streams	-0.0094	0.002	-4.115	0.000	-0.014	-0.005
Gender	0.5833	0.102	5.744	0.000	0.384	0.782
Age	0.0305	0.007	4.116	0.000	0.016	0.045
Work	-0.0871	0.028	-3.096	0.002	-0.142	-0.032
Degree	-0.0269	0.027	-1.009	0.313	-0.079	0.025
Reference	0.5892	0.149	3.964	0.000	0.298	0.881
Playstyle	-0.0019	0.001	-1.892	0.059	-0.004	6.91e-05
Residence_ISO3	0.0039	0.001	2.635	0.008	0.001	0.007
Birthplace_ISO3	-0.0033	0.001	-2.564	0.010	-0.006	-0.001

Table 9 : Statistics for Logistic Regression Anxiety Class Moderate

Anxiety Class=2	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0178	0.027	-0.657	0.511	-0.071	0.035
Platform	-0.7106	0.232	-3.066	0.002	-1.165	-0.256
Hours	0.0086	0.002	3.577	0.000	0.004	0.013
whyplay	0.0024	0.001	3.000	0.003	0.001	0.004
streams	0.0028	0.003	0.908	0.364	-0.003	0.009
Gender	-0.4668	0.125	-3.728	0.000	-0.712	-0.221
Age	-0.0002	0.011	-0.020	0.984	-0.022	0.022
Work	0.1166	0.040	2.932	0.003	0.039	0.195
Degree	0.0144	0.040	0.356	0.721	-0.065	0.094
Reference	-0.3600	0.206	-1.746	0.081	-0.764	0.044
Playstyle	0.0007	0.001	0.481	0.631	-0.002	0.003
Residence_ISO3	0.0011	0.002	0.512	0.609	-0.003	0.005
Birthplace_ISO3	-0.0010	0.002	-0.543	0.587	-0.005	0.003

Table 10 : Statistics for Logistic Regression Anxiety Class Severe

Anxiety Class=3	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0486	0.035	-1.405	0.160	-0.116	0.019
Platform	-0.3771	0.323	-1.167	0.243	-1.011	0.256
Hours	0.0159	0.003	5.455	0.000	0.010	0.022
whyplay	0.0014	0.001	1.313	0.189	-0.001	0.003
streams	0.0089	0.004	2.457	0.014	0.002	0.016
Gender	-0.7838	0.152	-5.152	0.000	-1.082	-0.486
Age	0.0154	0.014	1.071	0.284	-0.013	0.044
Work	0.2035	0.052	3.950	0.000	0.103	0.304
Degree	0.0161	0.055	0.295	0.768	-0.091	0.123
Reference	-0.9573	0.256	-3.736	0.000	-1.459	-0.455
Playstyle	0.0005	0.002	0.284	0.776	-0.003	0.004
Residence_ISO3	-0.0007	0.003	-0.240	0.811	-0.006	0.005
Birthplace_ISO3	0.0026	0.003	1.023	0.306	-0.002	0.008

Table 11 : Relevant summary Probabilistic Regression analysis for Anxiety Class

Probabilistic Regression for Anxiety Class:

OLS Regression Results

Dep. Variable:	Anxiety Class	R-squared (uncentered):	0.604
Model:	OLS	Adj. R-squared (uncentered):	0.604
Method:	Least Squares	F-statistic:	1232.
Date:	Tue, 09 Jul 2024	Prob (F-statistic):	0.00
Time:	11:25:06	Log-Likelihood:	-12227.
No. Observations:	10497	AIC:	2.448e+04
Df Residuals:	10484	BIC:	2.457e+04
Df Model:	13		
Covariance Type:	nonrobust		

Table 12 : Statistics for Probabilistic Regression Anxiety Class Minimal

Anxiety Class=1	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0264	0.019	-1.408	0.159	-0.063	0.010
Platform	-0.2092	0.181	-1.155	0.248	-0.564	0.146
Hours	-0.0025	0.002	-1.390	0.165	-0.006	0.001
whyplay	-0.0027	0.001	-5.279	0.000	-0.004	-0.002
streams	-0.0094	0.002	-4.114	0.000	-0.014	-0.005
Gender	0.5847	0.102	5.759	0.000	0.386	0.784
Age	0.0306	0.007	4.127	0.000	0.016	0.045
Work	-0.0870	0.028	-3.092	0.002	-0.142	-0.032
Degree	-0.0268	0.027	-1.005	0.315	-0.079	0.025
Reference	0.5770	0.149	3.883	0.000	0.286	0.868
Playstyle	-0.0019	0.001	-1.875	0.061	-0.004	8.59e-05
Residence_ISO3	0.0039	0.001	2.637	0.008	0.001	0.007
Birthplace_ISO3	-0.0033	0.001	-2.563	0.010	-0.006	-0.001

Table 13 : Statistics for Probabilistic Regression Anxiety Class Moderate

Anxiety Class=2	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0177	0.027	-0.651	0.515	-0.071	0.036
Platform	-0.6877	0.232	-2.969	0.003	-1.142	-0.234
Hours	0.0085	0.002	3.575	0.000	0.004	0.013
whyplay	0.0024	0.001	3.003	0.003	0.001	0.004
streams	0.0028	0.003	0.909	0.363	-0.003	0.009
Gender	-0.4665	0.125	-3.728	0.000	-0.712	-0.221
Age	-0.0002	0.011	-0.018	0.985	-0.022	0.022
Work	0.1166	0.040	2.932	0.003	0.039	0.195
Degree	0.0146	0.040	0.360	0.719	-0.065	0.094
Reference	-0.3736	0.206	-1.811	0.070	-0.778	0.031
Playstyle	0.0007	0.001	0.493	0.622	-0.002	0.003
Residence_ISO3	0.0011	0.002	0.514	0.607	-0.003	0.005
Birthplace_ISO3	-0.0010	0.002	-0.544	0.587	-0.005	0.003

Table 14 : Statistics for Probabilistic Regression Anxiety Class Severe

Anxiety Class=3	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0480	0.035	-1.387	0.165	-0.116	0.020
Platform	-0.3517	0.324	-1.087	0.277	-0.986	0.283
Hours	0.0159	0.003	5.457	0.000	0.010	0.022
whyplay	0.0014	0.001	1.337	0.181	-0.001	0.003
streams	0.0089	0.004	2.455	0.014	0.002	0.016
Gender	-0.7818	0.152	-5.137	0.000	-1.080	-0.484
Age	0.0158	0.014	1.096	0.273	-0.012	0.044
Work	0.2042	0.052	3.966	0.000	0.103	0.305
Degree	0.0167	0.055	0.305	0.761	-0.091	0.124
Reference	-0.9839	0.256	-3.845	0.000	-1.485	-0.482
Playstyle	0.0006	0.002	0.307	0.759	-0.003	0.004
Residence_ISO3	-0.0007	0.003	-0.237	0.812	-0.006	0.005
Birthplace_ISO3	0.0026	0.003	1.025	0.305	-0.002	0.008

Table 15 : Relevant summary statistics for Logistic Regression Satisfaction with Life Class

Logistic Regression for Satisfaction with Life Class (Multiclass):

MNLogit Regression Results

Dep. Variable:	Satisfaction with Life Class	No. Observations:	10497
Model:	MNLogit	Df Residuals:	10419
Method:	MLE	Df Model:	72
Date:	Tue, 09 Jul 2024	Pseudo R-squ.:	0.01996
Time:	11:25:10	Log-Likelihood:	-18634.
converged:	True	LL-Null:	-19013.
Covariance Type:	nonrobust	LLR p-value:	3.225e-115

Table 16 : Statistics for Logistic Regression Satisfaction with Life Class Slightly dissatisfied

Satisfaction with Life Class=1	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0352	0.039	0.894	0.371	-0.042	0.112
Platform	-0.8509	0.441	-1.928	0.054	-1.716	0.014
Hours	0.0017	0.004	0.433	0.665	-0.006	0.009
whyplay	0.0006	0.001	0.536	0.592	-0.002	0.003
streams	0.0085	0.005	1.582	0.114	-0.002	0.019
Gender	0.1235	0.204	0.606	0.545	-0.276	0.523
Age	0.0451	0.018	2.556	0.011	0.011	0.080
Work	0.2024	0.067	3.031	0.002	0.072	0.333
Degree	0.0905	0.059	1.525	0.127	-0.026	0.207
Reference	0.3696	0.338	1.094	0.274	-0.292	1.032
Playstyle	-0.0017	0.002	-0.822	0.411	-0.006	0.002
Residence_ISO3	0.0004	0.003	0.127	0.899	-0.006	0.007
Birthplace_ISO3	-0.0010	0.003	-0.359	0.720	-0.007	0.005

Table 17 : Statistics for Logistic Regression Satisfaction with Life Class Dissatisfied

Satisfaction with Life Class=2	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0071	0.040	0.178	0.859	-0.071	0.085
Platform	-0.5481	0.453	-1.211	0.226	-1.435	0.339
Hours	0.0062	0.004	1.551	0.121	-0.002	0.014
whyplay	0.0012	0.001	1.016	0.310	-0.001	0.003
streams	0.0108	0.005	1.992	0.046	0.000	0.021
Gender	0.0339	0.207	0.163	0.870	-0.372	0.440
Age	0.0571	0.018	3.197	0.001	0.022	0.092
Work	0.3856	0.067	5.738	0.000	0.254	0.517
Degree	0.0291	0.061	0.480	0.631	-0.090	0.148
Reference	-0.1643	0.343	-0.480	0.631	-0.836	0.507
Playstyle	-0.0007	0.002	-0.330	0.742	-0.005	0.003
Residence_ISO3	0.0025	0.003	0.756	0.449	-0.004	0.009
Birthplace_ISO3	-0.0025	0.003	-0.866	0.386	-0.008	0.003

Table 18 : Statistics for Logistic Regression Satisfaction with Life Class Extremely dissatisfied

Satisfaction with Life Class=3	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0024	0.043	-0.055	0.956	-0.087	0.082
Platform	-0.9014	0.474	-1.903	0.057	-1.830	0.027
Hours	0.0178	0.004	4.247	0.000	0.010	0.026
whyplay	0.0023	0.001	1.792	0.073	-0.000	0.005
streams	0.0187	0.006	3.302	0.001	0.008	0.030
Gender	-0.1129	0.227	-0.496	0.620	-0.559	0.333
Age	0.0836	0.019	4.425	0.000	0.047	0.121
Work	0.5961	0.071	8.347	0.000	0.456	0.736
Degree	0.0832	0.068	1.231	0.218	-0.049	0.216
Reference	-1.2667	0.358	-3.541	0.000	-1.968	-0.566
Playstyle	0.0017	0.002	0.756	0.450	-0.003	0.006
Residence_ISO3	0.0009	0.004	0.241	0.810	-0.006	0.008
Birthplace_ISO3	-6.884e-05	0.003	-0.021	0.983	-0.006	0.006

Table 19 : Statistics for Logistic Regression Satisfaction with Life Class Slightly satisfied

Satisfaction with Life Class=4	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0631	0.040	1.590	0.112	-0.015	0.141
Platform	-0.7031	0.445	-1.581	0.114	-1.575	0.169
Hours	-0.0020	0.004	-0.496	0.620	-0.010	0.006
whyplay	-0.0014	0.001	-1.197	0.231	-0.004	0.001
streams	0.0006	0.005	0.118	0.906	-0.010	0.011
Gender	0.3107	0.206	1.510	0.131	-0.093	0.714
Age	0.0197	0.018	1.108	0.268	-0.015	0.055
Work	0.0721	0.067	1.071	0.284	-0.060	0.204
Degree	-0.0418	0.059	-0.707	0.480	-0.158	0.074
Reference	1.1003	0.340	3.238	0.001	0.434	1.766
Playstyle	-0.0054	0.002	-2.495	0.013	-0.010	-0.001
Residence_ISO3	0.0005	0.003	0.165	0.869	-0.006	0.007
Birthplace_ISO3	-0.0001	0.003	-0.038	0.970	-0.006	0.005

Table 20 : Statistics for Logistic Regression Satisfaction with Life Class Satisfied

Satisfaction with Life Class=5	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0598	0.040	1.478	0.139	-0.019	0.139
Platform	-0.7883	0.447	-1.763	0.078	-1.665	0.088
Hours	-0.0095	0.004	-2.287	0.022	-0.018	-0.001
whyplay	-0.0028	0.001	-2.465	0.014	-0.005	-0.001
streams	0.0007	0.006	0.121	0.904	-0.010	0.012
Gender	0.5435	0.213	2.548	0.011	0.125	0.961
Age	0.0250	0.018	1.390	0.165	-0.010	0.060
Work	-0.0807	0.069	-1.169	0.243	-0.216	0.055
Degree	-0.0195	0.060	-0.326	0.744	-0.137	0.098
Reference	1.1770	0.344	3.421	0.001	0.503	1.851
Playstyle	-0.0038	0.002	-1.761	0.078	-0.008	0.000
Residence_ISO3	0.0051	0.003	1.566	0.117	-0.001	0.011
Birthplace_ISO3	-0.0045	0.003	-1.588	0.112	-0.010	0.001

Table 21 : Statistics for Logistic Regression Satisfaction with Life Class Extremely satisfied

Satisfaction with Life Class=6	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0675	0.049	1.390	0.165	-0.028	0.163
Platform	-1.0098	0.492	-2.053	0.040	-1.974	-0.046
Hours	-0.0025	0.005	-0.510	0.610	-0.012	0.007
whyplay	-0.0026	0.001	-1.947	0.052	-0.005	1.71e-05
streams	0.0035	0.006	0.538	0.590	-0.009	0.016
Gender	0.1479	0.243	0.608	0.543	-0.329	0.624
Age	0.0675	0.020	3.393	0.001	0.029	0.106
Work	-0.1232	0.082	-1.510	0.131	-0.283	0.037
Degree	0.0670	0.069	0.974	0.330	-0.068	0.202
Reference	0.3781	0.395	0.957	0.339	-0.397	1.153
Playstyle	-0.0065	0.003	-2.400	0.016	-0.012	-0.001
Residence_ISO3	0.0007	0.004	0.196	0.845	-0.007	0.008
Birthplace_ISO3	0.0010	0.003	0.296	0.768	-0.006	0.008

Table 22 : Relevant summary Probabilistic Regression analysis for Satisfaction with Life Class

Probabilistic Regression for Satisfaction with Life Class:
OLS Regression Results

Dep. Variable:	Satisfaction with Life Class	R-squared (uncentered):	0.758
Model:	OLS	Adj. R-squared (uncentered):	0.757
Method:	Least Squares	F-statistic:	2522.
Date:	Tue, 09 Jul 2024	Prob (F-statistic):	0.00
Time:	11:25:11	Log-Likelihood:	-20608.
No. Observations:	10497	AIC:	4.124e+04
Df Residuals:	10484	BIC:	4.134e+04
Df Model:	13		
Covariance Type:	nonrobust		

Table 23 : Statistics for Probabilistic Regression Satisfaction with Life Class Slightly dissatisfied

Satisfaction with Life Class=1	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0354	0.039	0.899	0.369	-0.042	0.113
Platform	-0.8496	0.441	-1.924	0.054	-1.715	0.016
Hours	0.0017	0.004	0.435	0.664	-0.006	0.010
whyplay	0.0006	0.001	0.541	0.588	-0.002	0.003
streams	0.0085	0.005	1.582	0.114	-0.002	0.019
Gender	0.1232	0.204	0.604	0.546	-0.276	0.523
Age	0.0451	0.018	2.558	0.011	0.011	0.080
Work	0.2022	0.067	3.028	0.002	0.071	0.333
Degree	0.0900	0.059	1.516	0.130	-0.026	0.206
Reference	0.3674	0.338	1.088	0.277	-0.295	1.029
Playstyle	-0.0017	0.002	-0.818	0.413	-0.006	0.002
Residence_ISO3	0.0004	0.003	0.127	0.899	-0.006	0.007
Birthplace_ISO3	-0.0010	0.003	-0.359	0.720	-0.007	0.005

Table 24 : Statistics for Probabilistic Regression Satisfaction with Life Class Dissatisfied

Satisfaction with Life Class=2	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0072	0.040	0.182	0.855	-0.071	0.085
Platform	-0.5483	0.453	-1.211	0.226	-1.436	0.339
Hours	0.0062	0.004	1.553	0.120	-0.002	0.014
whyplay	0.0012	0.001	1.021	0.307	-0.001	0.003
streams	0.0108	0.005	1.993	0.046	0.000	0.021
Gender	0.0338	0.207	0.163	0.870	-0.372	0.440
Age	0.0571	0.018	3.199	0.001	0.022	0.092
Work	0.3854	0.067	5.735	0.000	0.254	0.517
Degree	0.0286	0.061	0.472	0.637	-0.090	0.147
Reference	-0.1661	0.343	-0.485	0.628	-0.837	0.505
Playstyle	-0.0007	0.002	-0.326	0.744	-0.005	0.004
Residence_ISO3	0.0025	0.003	0.756	0.449	-0.004	0.009
Birthplace_ISO3	-0.0025	0.003	-0.866	0.387	-0.008	0.003

Table 25 : Statistics for Probabilistic Regression Satisfaction with Life Class Extremely dissatisfied

Satisfaction with Life Class=3	coef	std err	z	P>|z|	[0.025	0.975]
Game	-0.0023	0.043	-0.052	0.958	-0.087	0.083
Platform	-0.9015	0.474	-1.903	0.057	-1.830	0.027
Hours	0.0178	0.004	4.249	0.000	0.010	0.026
whyplay	0.0023	0.001	1.795	0.073	-0.000	0.005
streams	0.0187	0.006	3.302	0.001	0.008	0.030
Gender	-0.1140	0.227	-0.501	0.616	-0.560	0.332
Age	0.0836	0.019	4.425	0.000	0.047	0.121
Work	0.5958	0.071	8.344	0.000	0.456	0.736
Degree	0.0825	0.068	1.222	0.222	-0.050	0.215
Reference	-1.2667	0.358	-3.541	0.000	-1.968	-0.566
Playstyle	0.0018	0.002	0.758	0.448	-0.003	0.006
Residence_ISO3	0.0009	0.004	0.241	0.810	-0.006	0.008
Birthplace_ISO3	-6.804e-05	0.003	-0.021	0.983	-0.006	0.006

Table 26 : Statistics for Probabilistic Regression Satisfaction with Life Class Slightly satisfied

Satisfaction with Life Class=4	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0632	0.040	1.593	0.111	-0.015	0.141
Platform	-0.7044	0.445	-1.584	0.113	-1.576	0.167
Hours	-0.0020	0.004	-0.494	0.621	-0.010	0.006
whyplay	-0.0013	0.001	-1.193	0.233	-0.004	0.001
streams	0.0006	0.005	0.119	0.905	-0.010	0.011
Gender	0.3101	0.206	1.507	0.132	-0.093	0.713
Age	0.0197	0.018	1.108	0.268	-0.015	0.055
Work	0.0719	0.067	1.068	0.285	-0.060	0.204
Degree	-0.0423	0.059	-0.717	0.474	-0.158	0.073
Reference	1.1005	0.340	3.238	0.001	0.434	1.766
Playstyle	-0.0054	0.002	-2.493	0.013	-0.010	-0.001
Residence_ISO3	0.0005	0.003	0.165	0.869	-0.006	0.007
Birthplace_ISO3	-0.0001	0.003	-0.038	0.970	-0.006	0.005

Table 27 : Statistics for Probabilistic Regression Satisfaction with Life Class Satisfied

Satisfaction with Life Class=5	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0599	0.040	1.480	0.139	-0.019	0.139
Platform	-0.7873	0.447	-1.761	0.078	-1.664	0.089
Hours	-0.0095	0.004	-2.286	0.022	-0.018	-0.001
whyplay	-0.0028	0.001	-2.463	0.014	-0.005	-0.001
streams	0.0007	0.006	0.121	0.904	-0.010	0.012
Gender	0.5417	0.213	2.540	0.011	0.124	0.960
Age	0.0249	0.018	1.388	0.165	-0.010	0.060
Work	-0.0810	0.069	-1.173	0.241	-0.216	0.054
Degree	-0.0201	0.060	-0.336	0.737	-0.137	0.097
Reference	1.1776	0.344	3.422	0.001	0.503	1.852
Playstyle	-0.0038	0.002	-1.760	0.078	-0.008	0.000
Residence_ISO3	0.0051	0.003	1.566	0.117	-0.001	0.011
Birthplace_ISO3	-0.0045	0.003	-1.588	0.112	-0.010	0.001

Table 28 : Statistics for Probabilistic Regression Satisfaction with Life Class Extremely satisfied

Satisfaction with Life Class=6	coef	std err	z	P>|z|	[0.025	0.975]
Game	0.0677	0.049	1.393	0.164	-0.028	0.163
Platform	-1.0109	0.492	-2.055	0.040	-1.975	-0.047
Hours	-0.0025	0.005	-0.509	0.611	-0.012	0.007
whyplay	-0.0026	0.001	-1.944	0.052	-0.005	2.17e-05
streams	0.0035	0.006	0.539	0.590	-0.009	0.016
Gender	0.1493	0.243	0.614	0.539	-0.327	0.626
Age	0.0675	0.020	3.394	0.001	0.029	0.107
Work	-0.1234	0.082	-1.512	0.130	-0.283	0.037
Degree	0.0663	0.069	0.965	0.335	-0.068	0.201
Reference	0.3768	0.395	0.953	0.340	-0.398	1.152
Playstyle	-0.0065	0.003	-2.398	0.016	-0.012	-0.001
Residence_ISO3	0.0007	0.004	0.196	0.845	-0.007	0.008
Birthplace_ISO3	0.0010	0.003	0.296	0.767	-0.006	0.008

Table 29 : Wald test results for Anxiety Class using Logistic Regression

Wald Test Results for Anxiety Class:

Wald Statistics:	0	1	2
Game	-1.415346	-0.657029	-1.404579
Platform	-1.241328	-3.066127	-1.166656
Hours	-1.389991	3.576752	5.455433
whyplay	-5.291197	3.000404	1.312587
streams	-4.115163	0.908408	2.456556
Gender	5.744450	-3.728188	-5.151757
Age	4.116035	-0.019824	1.070869
Work	-3.095942	2.932299	3.949886
Degree	-1.008664	0.356497	0.294748
Reference	3.964004	-1.746344	-3.736151
Playstyle	-1.891722	0.480930	0.284341
Residence_ISO3	2.635109	0.511837	-0.239681
Birthplace_ISO3	-2.563646	-0.543267	1.022921

Table 30 : Wald test results for Anxiety Class using Probabilistic Regression

```
Wald Test Results forProbabilistic Regression:
Wald Statistics:                            0          1          2
Game             -1.407917 -0.650722 -1.386875
Platform         -1.155161 -2.969044 -1.086880
Hours            -1.389755  3.575111  5.456580
whyplay          -5.279368  3.003011  1.337352
streams          -4.114234  0.908890  2.455290
Gender            5.758697 -3.727544 -5.136770
Age               4.127184 -0.018428  1.095576
Work             -3.091978  2.931677  3.965614
Degree           -1.005119  0.360049  0.304640
Reference         3.883372 -1.811459 -3.844630
Playstyle        -1.875060  0.493223  0.306823
Residence_ISO3    2.637445  0.513938 -0.237225
Birthplace_ISO3 -2.563304 -0.543669  1.025211
```

Table 31 : Result for Hosmer test Anxiety and Satisfaction with life for logistic regression

```
Hosmer-Lemeshow Test for Anxiety Class:
Statistic: 1279.822867132382
p-value: 0.0

Hosmer-Lemeshow Test for Satisfaction with Life Class:
Statistic: 1996.9827596526345
p-value: 0.0
```

Table 32 : Wald test results for Satisfaction with life class using Logistic Regression

```
Wald Test Results for Satisfaction with Life Class:
Wald Statistics:                            0          1          2          3          4          5
Game             0.894184  0.177677 -0.055120  1.589698  1.478123  1.389774
Platform        -1.927652 -1.210718 -1.902616 -1.580609 -1.763094 -2.053043
Hours            0.433144  1.550759  4.247382 -0.496164 -2.287480 -0.510079
whyplay          0.536135  1.015831  1.791783 -1.196698 -2.465173 -1.947070
streams          1.581598  1.991940  3.301732  0.118442  0.120685  0.538347
Gender           0.605886  0.163491 -0.496438  1.509907  2.548294  0.608339
Age              2.556463  3.196650  4.425110  1.107913  1.389575  3.392877
Work             3.030954  5.737621  8.347234  1.071484 -1.168720 -1.509540
Degree           1.525037  0.480494  1.231125 -0.707035 -0.325945  0.973897
Reference        1.094379 -0.479649 -3.541107  3.238128  3.421035  0.956567
Playstyle       -0.821779 -0.329546  0.756230 -2.495192 -1.761293 -2.400409
Residence_ISO3   0.127146  0.756342  0.240758  0.165079  1.566457  0.195802
Birthplace_ISO3 -0.359110 -0.866355 -0.021341 -0.037843 -1.588484  0.295635
```

Table 33 : Wald test results for Satisfaction with life class using Probabilistic Regression

Wald Test Results for Satisfaction with Life Probabilistic Regression:

Wald Statistics:	0	1	2	3	4	5
Game	0.898639	0.182189	-0.052182	1.593186	1.480455	1.393323
Platform	-1.924337	-1.211068	-1.902802	-1.583639	-1.760846	-2.055383
Hours	0.435048	1.552686	4.249075	-0.494417	-2.286103	-0.508672
whyplay	0.541052	1.021290	1.794796	-1.193208	-2.463072	-1.943587
streams	1.582111	1.992540	3.302236	0.119054	0.121106	0.538730
Gender	0.604271	0.163297	-0.501406	1.506932	2.539731	0.613645
Age	2.557827	3.198508	4.424872	1.107921	1.387717	3.393534
Work	3.028417	5.735289	8.344283	1.068128	-1.173105	-1.512463
Degree	1.515625	0.471577	1.221713	-0.716704	-0.336182	0.964828
Reference	1.087893	-0.484770	-3.540837	3.238499	3.422317	0.953252
Playstyle	-0.818099	-0.326058	0.757937	-2.493128	-1.759946	-2.398073
Residence_ISO3	0.127029	0.756312	0.240562	0.164961	1.566108	0.195709
Birthplace_ISO3	-0.358563	-0.865866	-0.021093	-0.037556	-1.588111	0.296034

Table 34 : Result for Hosmer test Anxiety and Satisfaction with life for Probabilistic regression

```
Hosmer-Lemeshow Test for Anxiety Class:
Statistic: 1278.311413054431
p-value: 0.0

Hosmer-Lemeshow Test for Satisfaction with Life Class:
Statistic: 1996.7378383713874
p-value: 0.0
```

10. References

A. A. Rahman, L. I. Khalid, M. I. Siraji, M. M. Nishat, F. Faisal and A. Ahmed, *"Enhancing the Performance of Machine Learning Classifiers by Hyperparameter Optimization in Detecting Anxiety Levels of Online Gamers," 2021 24th International Conference on Computer and Information Technology (ICCIT), Dhaka, Bangladesh, 2021, pp. 1-5*, doi: 10.1109/ICCIT54785.2021.9689911.

Aggarwal, S., Saluja, S., Gambhir, V., Gupta, S., & Satia, S. P. S. (2020, February 1). *Predicting likelihood of psychological disorders in PlayerUnknown's Battlegrounds (PUBG) players from Asian countries using supervised machine learning*. Addictive Behaviors. https://doi.org/10.1016/j.addbeh.2019.106132

Anxiety disorders. (2023, September 27). https://www.who.int/news-room/fact-sheets/detail/anxiety-disorders

Bonnaire, C., & Baptista, D. (2019, February 1). *Internet gaming disorder in male and female young adults: The role of alexithymia, depression, anxiety and gaming type*. Psychiatry Research. https://doi.org/10.1016/j.psychres.2018.12.158

Cardoso, J. B., Ferreira, T., & Dores, A. R. (2021, April 1). *The psychological determinants of internet gaming disorder: Vulnerability to stress, psychological well-being, and comorbidity*. European Psychiatry. https://doi.org/10.1192/j.eurpsy.2021.458

Changchun Liu changchun.liu@vanderbilt.edu, Pramila Agrawal, Nilanjan Sarkar & Shuo Chen (2009) Dynamic Difficulty Adjustment in Computer Games Through Real-Time Anxiety-Based Affective Feedback, International Journal of Human-Computer Interaction, 25:6, 506-529, DOI: 10.1080/10447310902963944

Chitale, V., Baghaei, N., Playne, D. P., Li, Z., Zhao, Y., Erensoy, A., & Ahmad, Y. (2022, December 1). *The Use of Videogames and Virtual Reality for the Assessment of Anxiety and Depression: A Scoping Review*. Games for Health Journal. https://doi.org/10.1089/g4h.2021.0227

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction with Life Scale. Journal of Personality Assessment, 49, 71-75.

Egami, H., Rahman, S., Yamamoto, T., Wakabayashi, T., & Egami, C. (2022, October 24). Causal effect of video game play on mental well-being: a quasi-experimental study among Japanese population. https://doi.org/10.31234/osf.io/8y7cf

Gosztonyi, M. (2023, September 1). *Who are the gamers? Profiling adult gamers using machine learning approaches*. Telematics and Informatics Reports. https://doi.org/10.1016/j.teler.2023.100074

Graziosi, G. (2022, July 7). Video game industry not recession-proof as sales set to fall in 2022. CNBC. https://www.cnbc.com/2022/07/07/video-game-industry-not-recession-proof-sales-set-to-fall-in-2022.html

Han, X., Wei, L., Sun, Y., Hu, Y., Wang, Y., Ding, W., Wang, Z., Jiang, W., Wang, H., & Zhou, Y. (2021, December 29). *MRI-Based Radiomic Machine-Learning Model May Accurately Distinguish between Subjects with Internet Gaming Disorder and Healthy Controls*. Brain Sciences. https://doi.org/10.3390/brainsci12010044

Kowal, M., Conroy, E., Ramsbottom, N., Smithies, T. D., Toth, A. J., & Campbell, M. J. (2021, June 16). *Gaming Your Mental Health: A Narrative Review on Mitigating Symptoms of Depression and Anxiety Using Commercial Video Games*. JMIR Serious Games. https://doi.org/10.2196/26575

Lee, B. W., & Leeson, P. R. C. (2015). Online gaming in the context of social anxiety. *Psychology of Addictive Behaviors, 29*(2), 473–482. https://doi.org/10.1037/adb0000070

Lindsten, F., Schön, T. B., Svensson, A., & Wahlström, N. (2017). Probabilistic modeling–linear regression & Gaussian processes. Uppsala: Uppsala University, 7.

Marques, L. M., Uchida, P. M., Aguiar, F. O., Kadri, G., Santos, R. I. M., & Barbosa, S. P. (2023). Escaping through virtual gaming-what is the association with emotional, social, and mental health? A systematic review. *Frontiers in psychiatry*, *14*, 1257685. https://doi.org/10.3389/fpsyt.2023.1257685

Mehroof, M., & Griffiths, M. D. (2010, June 1). *Online Gaming Addiction: The Role of Sensation Seeking, Self-Control, Neuroticism, Aggression, State Anxiety, and Trait Anxiety*. Cyberpsychology, Behavior, and Social Networking. https://doi.org/10.1089/cyber.2009.0229

N. Gharpure and N. Gharpure, "Linking Mental Health and Gaming Using C-Support Vectors and Multilayer Perceptrons," 2022 4th International Conference on Circuits, Control, Communication and Computing (I4C), Bangalore, India, 2022, pp. 18-24, doi: 10.1109/I4C57141.2022.10057920.

Pangistu, L. A. M., & Azhari, A. (2021, July 31). *Deep Learning on Game Addiction Detection Based on Electroencephalogram*. Jurnal Media Informatika Budidarma. https://doi.org/10.30865/mib.v5i3.3061

S. Salmani, P. Desale and F. Anthony, *"Analysis of Anxiety and Depression in Gaming Individuals," 2021 International Conference on Communication information and Computing Technology (ICCICT), Mumbai, India, 2021, pp. 1-5,* doi: 10.1109/ICCICT50803.2021.9510061.

Sauter, M., & Draschkow, D. (2017). Are Gamers Sad and Isolated? A database about the Anxiety, Life Satisfaction and Social Phobia of over 13000 participants.

Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: the GAD-7. Archives of internal medicine, 166(10), 1092-1097.

Stavropoulos, V., Zarate, D., Prokofieva, M., Van De Berg, N., Karimi, L., Alesi, A. G., Richards, M. A., Bennet, S., & Griffiths, M. D. (2023, December 22). *Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning*. Journal of Behavioral Addictions. https://doi.org/10.1556/2006.2023.00062

Stoltzfus, J. C. (2011). Logistic regression: a brief primer. Academic emergency medicine, 18(10), 1099-1104.

The Economist. (2023, March 20). Ready player four billion: The rise of video games. TheEconomist.https://www.economist.com/special-report/2023/03/20/ready-player-four-billion-the-rise-of-video-games

Wang, C., Wu, Y., Su, C. H., Lin, P. C., Ko, C., & Yen, J. Y. (2017, December 1). *Association between Internet gaming disorder and generalized anxiety disorder*. Journal of Behavioral Addictions. https://doi.org/10.1556/2006.6.2017.088