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BEHAVIORAL PATTERNS IN ONLINE GAMBLING IDENTIFIED THROUGH ARTIFICIAL INTELLIGENCE AND PSYCHIATRIC METHODS

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This study examined behavioral patterns in online gambling by using advanced technologies such as artificial intelligence (AI), machine learning, and the Internet of Behavior (IoB). The digital revolution has significantly increased access to online gambling, leading to the emergence of complex behavioral patterns among players. While many enjoy gambling as a form of recreation, the growing availability of online gambling poses a risks of addiction. The key role of AI and machine learning lies in the early detection of risky behavior among players. Algorithms can analyze gameplay data to identify patterns indicative of problematic behavior, including excessive spending and "chasing losses", which is the tendency to continue gambling or increase bets to recover losses. Appropriate interventions at the right time can mitigate the risk of developing gambling addiction. This research specifically focused on the use of machine learning and neural networks Multilayer Perceptron (MLP) to identify different player types, analyzing data from a group of online slot game players in the Republic of Srpska. Based on experience in clinical practice, models were trained on a sample of 200 players and tested on a broader group of 11,657 players to predict the risky behavior of players who played online slot games. Future research directions suggest the implementation of personalized tools for player control and support, with an emphasis on promoting responsible gambling and protecting public health. The results were evaluated using player data from the Republic of Srpska, a market governed by regulations designed to protect online gambling participants. This analysis underscored the role of regulatory frameworks and educational initiatives in mitigating the risk of gambling addiction.

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Key words: *behavioral patterns, Internet of Behavior, online gaming addiction, public health, artificial intelligence*

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Introduction

In the era of the digital revolution, online gambling is becoming increasingly widespread, creating complex behavioral patterns. These patterns, viewed through psychiatric methods and advanced artical intelligence (AI) technology, as well as through the concept of the Internet of Behavior (IoB), raise new questions and challenges in understanding human nature. Online gambling has been available since the mid-1990s. For some individuals, it serves as a form of entertainment and recreation, comparable to going to the cinema, whereas others perceive online gambling as a hobby. Unlike traditional casinos, online games are accessible from any location, without social stigma, and at any time of day, allowing players to spend more time gambling, thus providing an enjoyable experience.

These factors increase both the frequency and duration of play. As online gambling has an increase in popularity, the demand for systems that monitor player behavior has arisen, driven by the social responsibility to safeguard players. Global trends indicate that through the regulation of online gambling and the introduction of laws and measures to protect players, there is an effort to promote this as a recreational activity a fun and recreational industry, rather than an impulse control disorder.

In many countries around the world, online gambling is considered a socially acceptable and legal form of entertainment. However, the availability of online gambling raises public health concerns due to the potential for contributing to the development of addiction. Recently, gambling addiction has increasingly attracted the attention of clinicians and researchers. Therefore, it is crucial to identify players who are at high risk of developing problematic gambling behavior as early as possible. Behavioral indicators and AI can predict the development of gambling addiction with high accuracy.

Addiction typically entails exposure to a particular stimulus, which is then followed by behavior directed at reliving that experience. After a certain number of repetitions, addiction is established. The nature and frequency of addiction can fluctuate over time and may occasionally be disrupted by the individual's efforts to regain control. Problematic gambling manifests as repetitive behavior, in which individuals are unable to control their betting activities. Regulators worldwide aim to make online gambling an entertainment industry, rather than a public health issue.

Pathological gambling (1), as a form of addiction, is the most widespread and severe type of non-substance addiction. This disorder is characterized by an overwhelming urge to gamble, which exceeds the boundaries of social or recreational activity, and it is accompanied by a willingness to risk money to achieve greater gain. Addictions are often associated with impulsive behavior. Historically, pathological gambling was considered an impulse control disorder, but it has recently been reclassified as a behavioral addiction within the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) (2) and International Classification of Diseases, 11th Revision (ICD-11) (3). This type of gambling is recognized as a specific addiction disorder of global proportions, manifesting through an uncontrollable need to gamble, leading to serious consequences for a person’s mental and physical health, as well as negative effects on other aspects of their life. Artical intelligence (AI) algorithms analyze player behavior to recognize patterns indicative of problematic behavior, such as excessive spending or extended periods of gameplay. Identifying these issues at on early stages enables timely interventions and support for players whose behavior may escalate into more severe gambling problems.

The COVID-19 pandemic had a significant impact on gambling in many jurisdictions worldwide. Literature review on online gambling during the pandemic (4) systematically identified and described survey findings regarding the effects on gambling behavior and gambling disorders during the pandemic.

This paper examines behavioral patterns in online gambling, using psychiatric methods in combination with machine learning, AI, and the IoB concept. Internet of Behavior (IoB) refers to the collection of data that provides key insights into user behavior, interests, and preferences. From the perspective of behavioral psychology, IoB seeks to understand data generated by user activities on the internet. This study analyzed individual player activity data from the Republic of Srpska to determine whether a player belonged to the category of recreational slot game players, displaying no signs of addiction, or showing indications of risky behavior or clear signs of addiction. The application of AI to these analyses at an early stage enabled the reliable prediction of addiction risk, allowing for timely interventions to prevent its progression.

One of the goals of this study was to identify playing patterns by tracking the behavior of active players in the Republic of Srpska over 12 weeks of playing online slot games. The study was conducted to identify behavioral markers that can predict the occurrence of problematic gambling. The dataset was obtained from an online slot game provider, encompassing over two hundred different games available through multiple operators in the Republic of Srpska. The data was provided in accordance with a Non-Disclosure Agreement, preventing the sharing of details or the identification of individual players.

Previous research has encountered difficulties in identifying at-risk players, primarily due to the absence of clinical verification, relying instead on self-reported cases of problematic gambling behavior. In this study, Multilayer Perceptron (MLP) 200 players were analyzed and categorized by experts in addiction psychology and psychiatry. The players were categorized into recreational players, those showing signs of risky behavior, and those showing clear signs of addiction. Machine learning was applied to this sample using a neural network, specifically an MLP, which was then tested on a control group of 11,657 players to identify these player types in the Republic of Srpska.

The study presents an overview of previous research, challenges in developing machine learning models, and detecting problematic player behavior, as well as directions for future research. The proposed solution includes selecting relevant behavioral pattern markers and training machine learning models. The implementation of the Multilayer Perceptron (MLP) algorithm for supervised machine learning and the detection of risky player behavior was carried out using clinical experience in selecting harmful behavioral markers.

Previous Research

In recent years, the number of projects utilizing AI, and IoB has increased significantly. However, only a small portion of these projects focuses on improving public health and preventive measures for online slot players. Most research primarily concentrates on player behavior monitoring, with only a few examining the influence of various factors identified through the analysis of behavioral patterns, as defined by psychiatric methods. Since online slot players face different levels of risk for developing gambling disorders, there is a need to develop more tools and resources to mitigate the harmful consequences of gambling. Previous research has emphasized the importance of accuracy in machine learning algorithms, highlighting the need to balance the prevention of the negative effects of gambling with the preservation of privacy while minimizing the use of sensitive data. The approaches analyzed have also considered the ethical application of AI in the gambling industry, particularly regarding voluntary self-exclusion programs and responsible gambling initiatives that allow players to voluntarily limit their access to games. However, no new methods have been proposed. The data analyzed generally consisted of a limited set of indicators, and comprehensive statistics on the proportions of recreational, at-risk, and problematic players were often lacking. Additionally, players from multiple operators within the same country were not included in these analyses.

Behavioral addictions, particularly online gambling, internet addiction, and gaming disorder, are increasingly recognized as significant public health challenges, as noted in reference (5). While not all behavioral addictions are yet formally classified in systems like ICD-11 or DSM-5, online gambling and gaming disorder have gained official recognition. Online gambling is classified as a mental disorder in ICD-11, and more recently, gaming disorder has been added as a new category. Various countries, especially in Europe and parts of Asia, have begun developing national strategies and opening treatment centers to address these issues. Research highlights the importance of early intervention, education, and prevention campaigns, particularly targeting youth.

A study conducted in 2012 examined the potential for early identification of players at high risk of developing gambling problems by analyzing their behavior during the first month of play (6). The study hypothesized that behavioral markers such as gambling frequency, intensity, and the tendency to increase or decrease bets during the first month of live play could segment players who would later close their accounts due to problematic gambling. A sample of over 48,000 sports bettors was segmented using K-means cluster analysis into groups with similar gambling patterns. Out of 48,000 players, 1,758 closed their accounts after one month of play. Of these, 530 (33%) confirmed they had closed their accounts due to gambling problems, 19% were dissatisfied with the gambling provider's services, and 48% stated they were no longer interested in gambling. Participants were residents of Germany, Turkey, Poland, and Spain. The findings revealed that only a small percentage (3%) of those who closed their accounts due to gambling-related issues belonged to the high-risk group, highlighting the complexity of early detection and the need to improve player segmentation algorithms.

An earlier study (7) analyzed data from 22,500 players in England to explore the role of gender in predicting problematic gambling behavior. It emphasized the importance of recognizing gender-specific behavioral patterns and their potential link to risk-taking tendencies. It was suggested that testosterone levels could be linked to risk-taking behavior and pathological gambling, and gender-based behavioral patterns in problematic gambling were identified. Using the Random Forest algorithm (8), researchers developed a model in which gender served as the primary classification variable. To address concerns about using gender data directly, they proposed training separate models for each gender and merging them into a final model that does not require gender as an input, while still preserving predictive accuracy.

BetBuddy (9) used risk curve analysis to identify online players whose behavior resembled that of those who had self-excluded from gambling. Focusing on UK players of bingo and slot games, the model evaluated behavioral indicators such as nighttime play and declined deposits. The dataset used for training the model included variables describing playing behavior, deposits, withdrawals, and player-set limits. Findings showed that certain behaviors, like moderate night time gambling or frequent deposit refusals, were not inherently problematic unless combined with other risk factors. Using a Random Forest algorithm, the model effectively predicted self-exclusion risk and demonstrated potential for harm reduction by enabling timely interventions and supporting the development of safer gambling guidelines.

A study using data from a Canadian gambling operator tested the performance of machine learning, specifically the Random Forest algorithm, in classifying online gambling players with a history of self-exclusion (10). The model was trained on behavioral data such as frequency, intensity, and variability of play, with bet variability per session emerging as the most significant predictor. Of all the input variables, bet variability per session was the most significant for prediction, contributing 32% to the predictive signal. While psychological factors like “chasing losses”, were not included, the model demonstrated solid predictive accuracy, confirming the potential of behavioral data for identifying self-excluding players.

A review from 2011 highlighted key challenges in using machine learning for predicting online gambling disorders. It emphasized that commonly used indicators, such as self-exclusion or account closure, were insufficient on their own and should be complemented by behavioral and contextual variables, including demographics, deposit patterns, night-time play, and customer support interactions (11). The review also stressed the importance of tracking bet escalation to detect behaviors like "chasing losses." A central challenge remains the integration of data science insights with psychological theories to better understand cognitive processes, such as impulsivity, and their role in problem gambling.

Seo et al. explored the use of machine learning to detect problematic gambling among adolescents in South Korea, aiming to support early prevention (12). Based on survey data from over 5,000 students, key predictors included recent online gambling activity, peer betting, and gambling-related behaviors and demographics. Four models were trained: Random Forest, Support Vector Machine (13), Extra Trees (14), and Ridge Regression (15), with Random Forest showing the highest reliability in predictions. Algorithms trained on a sample of 5,045 students provided moderate accuracy in predicting problematic gambling. Of the 5,045 participants, 51.1% were male, 48.9% female, with an average age of approximaty 15 years. Among the tested models, Random Forest demonstrated the highest predictive reliability. Although mental stress was not included, results highlighted the influence of psychological, social, and environmental factors. The study recommended gambling education for both adolescents and parents, and proposed implementing the model in mobile apps to enable self-assessment of gambling risk.

In 2020, Auer M et al. analyzed data from 70,789 players of a Norwegian operator to predict changes in self-imposed monetary limits using machine learning (16). Only 6.7% of players adjusted their monthly loss limits, with most increases occurring after receiving feedback that 80% of the limit had been reached, which often resulted in greater losses. Among players who received feedback that they had reached 80% of their spending limit, 18% adjusted their limit, most often increasing it, while only 0.7% lowered it. Ten percent of players selected the maximum monthly spending limit, and 5% were classified as problematic gamblers. Key predictors included prior limit increases, total wagers, theoretical loss, and feedback messages. Machine learning algorithms used included Logistic Regression (17), Linear Discriminant Analysis (18), Random Forest, Gradient Boost Machine Learning (19), and Naive Bayes (20). Among the tested algorithms, Gradient Boost outperformed others in predicting limit changes. The study highlighted the potential of predictive analytics to support timely and personalized responsible gambling interventions.

It is important to note that most previous studies were based exclusively on data from a single operator in a single country. Such data provide only a partial view of behavioral patterns during playing the online slots, excluding other operators. Previous studies did not involve clinical professionals, nor did they consider the mentality and habits of a particular population when selecting harmful markers for machine learning model training. Several hypotheses have been proposed regarding which types of online gambling are more strongly associated with harmful behavioral markers and which have a higher potential to encourage risky behavior as player engagement increases. Behavioral markers leading to future self-exclusion were analyzed, as well as whether the monetary characteristics of players' gambling further improve prediction. Methodologically, supervised learning was used relatively more frequently than unsupervised learning in the included addiction studies. In earlier studies, models such as Random Forest, Logistic Regression, Linear Discriminant, Naive Bayes, and Gradient Boosting Machine were used. The Random Forest model achieved the highest training accuracy, exceeding 90%, while testing accuracy was below 80%. Other models demonstrated significantly lower accuracy during training and testing, i.e., below 80%.

By proposing multiple hypotheses in this study, several goals were achieved, which will be described in the following sections. Harmful behavioral markers were selected for slot players. Using IoB and machine learning algorithms, data were interpreted with the aim of reducing the negative impact on mental health and creating a positive impact on overall well-being by preventing risky players from escalating. The model was trained and evaluated using data obtained from an online slot game provider, with a portfolio of 279 different slot games played across various online gambling operators in the Republic of Srpska, and a database of 11,857 players.

Dataset and Methodology

Using markers derived from psychiatric methods and clinical practice, the objective was to train a machine learning model with data from recreational players, those demonstrating risky behavior, and players showing problematic gambling behavior.

The dataset was obtained from an online slot game provider, featuring a portfolio of over two hundred different slot games. Slot games have shorter event frequencies, minimal pauses between bets, enable continuous betting opportunities, facilitate impulsive decision-making, and are highly accessible, playable at any time of day or night. These slot games are played across various online operators within the Republic of Srpska. When considering both the training and testing datasets, 279 games and 11,857 players were processed. The model was trained on a sample of 200 players and tested on 11,657 players. The data was provided under a Non-Disclosure Agreement, which prevents sharing or reporting individual player data. The player's behavior information was anonymized, ensuring that no individual could be identified or traced in any way. The raw data included every game played and every bet placed between January and April 2024. For the model training and subsequent predictions, randomly selected players who played during that period and participated in at least one session per week were included. Millions of individual game rounds were aggregated through sessions, days, and weeks for each player to extract relevant behavioral markers. A session is defined as a continuous period of play in which the player places successive bets within a specific time frame.

The dataset, consisting of a total of 15,413.076 individual rounds (bets) played in slot games, was grouped by weeks for each individual player. The raw data was aggregated such that for each data point in the dataset, 10 input variables, i.e., behavioral markers, were generated for model training, with one output variable as the result. The information about the dataset used for training the neural network to detect player behavioral patterns is as follows:

- Country: Republic of Srpska
- Legally regulated online gambling: Yes
- Number of analyzed games: 279
- Number of players: 200
- Number of individual rounds/spins: 15,413,076
- Number of training samples: 2,400.

Behavioral Markers

Harmful behavioral indicators play a critical role in implementing responsible gambling strategies, enabling personalized interventions for players. It is expected that such tailored interventions will more effectively raise awareness, reduce risky behavior, and prevent harmful outcomes. Certain characteristics can be grouped to monitor specific activities, trends, or fluctuations in player behavior over time. For example, the number of minutes a player spends gambling daily, the increase in average playing time over a certain period, and variations in playtine throughout the day can indicate risk. Nighttime gambling is especially risky, as it often indicates that players may be making irrational decisions, which can adversely impact their work and personal life. Frequent gambling is associated with impulse control disorders, while stable betting amounts may indicate better control, whereas dramatic shifts in bets signal potential problems. Additionally, tracking the amount of money players spend, their wins and losses lover a one-week period, helps in analyzing the frequency, intensity, session duration, and variability. Frequency refers to the number of sessions within a given period, intensity to the length of the sessions and behavior during them, while variability indicates changes in player behavior, such as "chasing losses". Changes in these indicators over time enable the identification of shifts in gambling behavior.

Multiple variables are included in the model to achieve optimal prediction. Behavioral indicators can be divided into those tracking activity levels (such as the number of minutes spent gambling daily) or those analyzing trends over time (e.g., an increase in average daily playing time over the past month) and variability (e.g., changes in playing time throughout the day or shifts in betting amounts). To maximize model performance, a diverse range of characteristics and variables is necessary.

After extracting the markers, the challenge was to identify the most relevant ones for grouping players and classifying their risk-pronebehavior. Precise selection of behavioral indicators is crucial for the rapid and accurate training of the model to provide reliable predictions.

During the marker selection process, with clinical practice as a foundation, 10 key input variables were chosen for training the machine learning model. All variables were numerical, and the output classified players as follows: 0—recreational players, 1—at-risk players, and 2—problematic players. According to psychiatric methods, players were divided into three groups. The first group consists of those who play infrequently, with low bets and minimal bet variability. The second group includes players who play more frequently and intensively, but with stable bets. The third group involves players who gamble more intensively, with significant fluctuations in their betting amounts.

Recreational players, categorized in the first group, typically do not play more than two games simultaneously, place small bets, and their sessions last less than two hours. The time between their gombling sessions and rounds is consistent, and their bets remain stable. At-risk and problematic players engage in shorter sessions with higher bets that often increase, while the time between sessions is very short. Their bets and volatility fluctuate significantly compared to average values. The key difference between the second and third groups lies in larger bets, greater session variability, night-time gambling, and shorter intervals between sessions.

Sampling and Statistical Analysis

As previously mentioned, player behavior was monitored for training and validation the machine learning model, with players selected randomly. The dataset used for training and validating the model tracked 200 players over 12 weeks, resulting in 2.400 samples, each containing 10 input markers. The samples were labeled based on psychiatric methods and clinical practice, and grouped into non-risky, at-risk, and problematic gombling behavior categories. The dataset was split into a training set (80% of the samples) and a validation set (20% of the samples).

Demographic and statistical Data for the Republic of Srpska:

- Total population (millions): 1.2 (21)
- Average monthly net salary in 2024 (EUR): 710.2 (22)
- Unemployment rate in 2024: 11.2% (23)
- Literacy rate in 2024: 96.8% (24)
- Internet penetration rate: 83% (25)
- Percentage of the population engaged in gambling activities: 15% (26).

According to available data (27), the religious composition in the Republic of Srpska is as follows:

- Eastern Orthodox Christianity: 82%
- Islam: 12.76%
- Catholicism: 2.20%
- Protestantism: 0.02%

●Other Christian denominations: 0.21%
●Other religions: 0.49%
●Agnosticism: 0.10% and
●Atheism: 0.50%.

Online gambling is regulated by law in the Republic of Srpska. As online gambling is legally governed, players engage with licensed gambling operators (28).
However, there are no mandatory measures to enforce responsible gambling practices.

Dataset for Training the Model for Players in the Republic of Srpska

In the dataset comprising 200 players, with 12 weeks of data per player, a total of 15,413,076 individual bets were aggregated for training the model for the territory of the Republic of Srpska.

For those classified as extreme cases, the average nightly playtime was approximately 3 hours, while the 24-hour average was around 5.4 hours per day. Additionally, the following were obtained:

●The average number of different games played per week was approximately 4.

●The average number of rounds per day was 2,868.

●The average daily loss was around 229 BAM.

●The average daily bet amount was approximately 2,368 BAM.

For players considered at risk, the average nightly playtime was around 40 minutes, and the 24-hour average was approximately 1.4 hours per day. Additionally, the following were obtained:

●The average number of different games played per week was around 3.

●The average number of rounds per day was approximately 534.

●The average daily loss was around 6 BAM.

●The average daily wage was close to 65 BAM.

Considering the average net salary in the Republic of Srpska, cultural norms, customs, and the population's mentality, as well as insights from psychiatric practice, it is concluded that more than five hours of gambling per day constitutes problematic gambling. Additionally, any daily wager exceeding 60 BAM goes beyond recreational play and enters the at-risk category. A continuous weekly loss exceeding 120 BAM, combined with "chasing losses" and high bets, is an indicator of problematic gambling. Playing four or more different games daily is considered extreme. An average of more than two hours of nighttime gambling indicates a high risk of impulse control disorders. If all observed parameters increase or fluctuate significantly over the 12-week observation period, the player's behavior transitions into the category of players at-risk players with behavior. Any extreme variations in intensity, frequency, variability, or session length indicate a loss of control by the player.

The dataset used to train the model for the Republic of Srpska was imbalanced, consisting of 31% recreational players, 41% players at-risk, and 28% problematic players, as determined after the samples were labeled by experts with clinical experience in the fields of psychology and addiction psychiatry.

Proposed Solution

For a long time, AI has played an important role in player protection systems against the negative consequences of gambling, with its application significantly increasing over the past year. Platforms now frequently use machine learning models for player prediction and segmentation, offering standardized approaches. Generative artificial intelligence enables the creation of personalized content for each player. In the future, machine learning is expected to advance with a deeper understanding of player behavior while considering legal regulations related to the use of AI in areas like gambling.

In previous research, a key obstacle to identifying players with risky behavior was the lack of external verification, as there was no clinical identification of the samples used for model training. Instead, researchers relied on players who self-identified their behavior as problematic and stopped gambling, and their behavioral indicators were used to train machine learning models. In this study, players from the Republic of Srpska were analyzed, with their behavior classified by experts in psychology and addiction psychiatry. The behavior of each player in each week was labeled as non-risky, at-risk, or problematic, and this data was then used to train the machine learning model. In classifying behavior, factors such as average net salary, culture, customs, and the local population's mentality, along with insights from psychiatric practice, were considered.

The most prominent characteristics of at-risk players included frequent and intense gambling, as well as significant variations in bets. A noticeable pattern was the players' need to increase bets to achieve the excitement they once gained with smaller bets, while attempts to recoup losses were identified as an indicator of pathological gambling. Changes in bets serve as a significant indicator for distinguishing at-risk from non-risky players, as most recreational players show consistent playing patterns. Another important indicator is playtime, how often a player gambles at night, and whether they are more active on weekdays or weekends. The logic behind this is that players with less control over their behavior tend to gamble more frequently at night, attempting to hide these activities from others.

Machine learning models vary in complexity. Innovations in machine learning research often focus on new techniques for processing large datasets. The aim of this study was not to introduce new machine learning techniques for improved prediction but rather to apply an existing predictive model to the topic of player behavior prediction and risk assessment, specifically trained for the Republic of Srpska, to promote responsible gambling. Unlike most previous studies that used Random Forest, this study employed a neural network approach, specifically MLP classification. The MLP model was trained on an imbalanced dataset of randomly selected data samples.

To develop and train the model in the most appropriate way, it was necessary to bring together expertise from multiple fields. In this study, the training data were prepared, and the machine learning model was trained and tested with the help of experts in software engineering and addiction psychiatry.

For each individual player, every bet placed was stored in the database. By aggregating such raw data, every round played by the player over a specific week, a set of input variables was created to describe the player’s behavior, frequency, intensity of play, and time spent gambling during that week. Repeating this process for each player over a 12 weeks period resulted in a set of input variables for training, validating, and testing the MLP model.

The set of input variables resulting from the aggregation and processing of individual rounds included: player ID, number of the week of the year, number of different games played, total loss, average daily playtime, average number of daily rounds, total wager, total morning playtime, total daytime playtime, and total night-time playtime. Morning, daytime, and night-time play were categorized within the time frames of 6:00 AM to 12:00 PM, 12:00 PM to 7:00 PM, and 7:00 PM to 6:00 AM, respectively.

For model training and validation, a total of 2,400 data samples were aggregated, representing 200 randomly selected players with behavioral data over a 12 weeks period. Each week, for each individual player, was labeled by an expert with domain knowledge in clinical practice and psychiatric methods for identifying addiction, classifying player behavior with output variable values of 0, 1, or 2 for recreational play, risky play, and problematic play, respectively. The test set for the model, i.e., the control group of players, consisted of a total of 139,884 previously unseen samples of behavioral data, representing the behavior of 11,657 players per week over 12 weeks.

Model Architecture

The artificial neural network (ANN), specifically the MLP model used in this study, was designed with an input layer, two hidden layers, and an output layer. Experimental methods were employed to determine the most suitable model architecture that would provide the highest accuracy. The best results were obtained with the number and arrangement of neurons per layer, as shown in Figure 5. The input layer consists of 13 neurons, the first hidden layer has 22 neurons, and the second hidden layer has 11 neurons. The output is a single neuron with three possible values (recreational behavior, at-risk behavior, and problematic behavior).

The trained MLP model achieved an accuracy of 99.446% during training and 95.928% during testing. Between 50 and 200 epochs, the test loss and test accuracy remained relatively stable at approximately 96.83% accuracy. From 250 to 400 epochs, there was a slight improvement in testing accuracy, reaching 97.29%, indicating performance improvement. After that, training between 500 and 700 epochs showed an increase in test loss and a decrease in testing accuracy, indicating potential overfitting. Between 800 and 1,000 epochs, test losses continued to rise, and testing accuracy fluctuated between 95.48% and 95.93%, indicating that overfitting likely began between 600 and 700 epochs.

Model’s Confusion Matrix

In this case, since the model has three output values (classes), the confusion matrix is 3x3 and displays the performance of the classification model. The rows represent the true classes, i.e., the labels, while the columns represent the predicted classes. Each cell (c[i,j]) in the matrix shows the number of instances of class iiii that were predicted as class jjj.

●Class 0. A total of 125 instances were correctly classified. Only 1 instance was incorrectly classified as class 1, while 0 instances were incorrectly classified as class 2.

●Class 1. A total of 20 instances were correctly classified. A total of 5 instances were incorrectly classified as class 0, while 2 instances were incorrectly classified as class 2.

●Class 2. A total of 67 instances were correctly classified. A total of 0 instances were incorrectly classified as class 0, while 1 instance was incorrectly classified as class 1. Figure 1 illustrates the confusion matrix for the classification algorithm's performance evaluation.

It is concluded that the model performs very well for classes 0 and 2, while it makes slight errors with class 1, having difficulty distinguishing class 1 from classes 0 and 2. The model more easily identifies recreational and problematic players with clear signs of addiction, while at-risk players are the most difficult to recognize

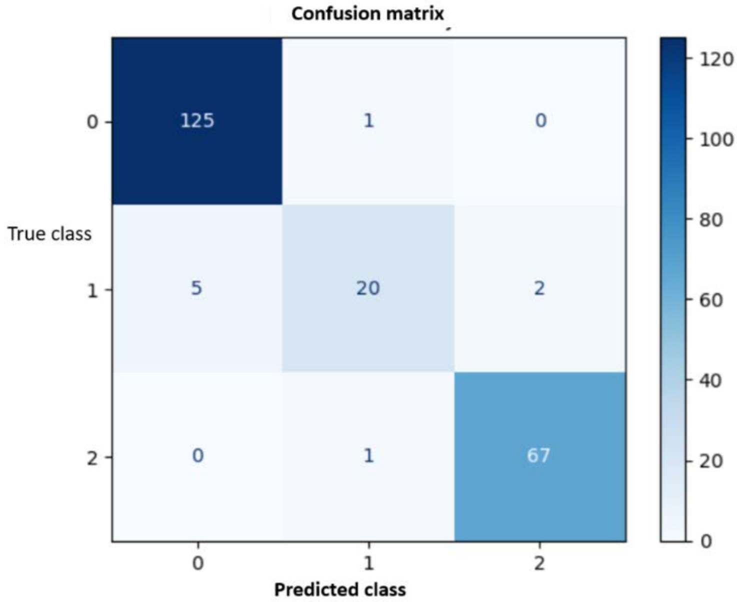

Figure 1. Confusion Matrix from model training on players in the Republic of Srpska

Table 1. Overview of Confusion Matrix Metrics for the trained model for players from the Republic of Srpska

Metrics	Class 0	Class 1	Class 2
Recall	99.21%	80%	98.53%
Accuracy	96.15%	95.24%	97.10%
Specificity	94.74%	98.97%	98.69%
Prevalence	57.27%	11.36%	31.36%
F score	97.65%	85.11%	97.10%

ROC Curve

Receiver Operating Characteristic (ROC) Curves show metrics like accuracy and precision, which are good indicators when the data is balanced. For an imbalanced dataset, high accuracy does not necessarily mean the classifier is effective. For example, if 90 out of 100 players are recreational, even if the algorithm classifies all 100 as recreational, its accuracy would be 90%, which could give a misleading impression of the model's performance. In cases of imbalanced datasets, metrics like ROC are more effective for evaluation. The ROC curve visually represents the performance of a binary classification model at various classification thresholds. It is a plot of the true positive rate (TPR) versus the false positive rate (FPR), calculated as specificity at different threshold values. The point closest to the 45-degree line on the graph is considered the most accurate threshold. If the threshold is too high, there will be fewer false positives, but more false negatives, and vice versa.

●Class 0: A TPR (precision) of 99.21% and an FPR of 5.26% indicate that the model classifies class 0 instances very well.

●Class 1: A TPR of 80.00% and an FPR of 1.03% suggest that the model identifies class 1 with sufficient precision, but there is room for improvement.

●Class 2: A TPR of 97.10% and an FPR of 1.31% show that the model performs excellently for class 2.

Classes 0 and 2 have AUC (Area Under the ROC Curve) values close to 1, indicating excellent performance. Class 1 has a slightly lower AUC, reflecting a trade-off between detection probability and specificity.

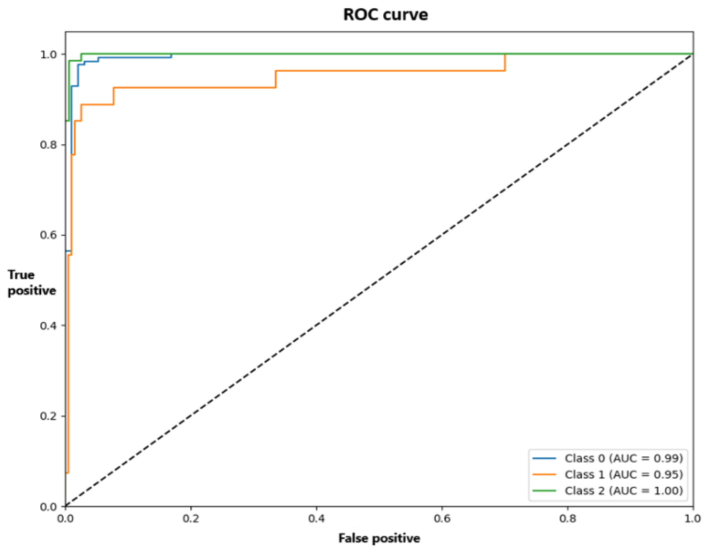

Figure 2. ROC Curve for the model trained for players from the Republic of Srpska

Evaluation and Discussion

The main objective of this study was to discover behavioral patterns related to online gambling, identified through psychiatric methods in combination with artificial intelligence and IoB. To achieve this goal, it was necessary to implement and evaluate an algorithm for detecting the harmful effects of online gambling.

The dataset, comprising a total of 268,062,490 individual bets placed in slot games, was grouped by weeks for each individual player. The test set for the model, i.e., the control group of players, consisted of a total of 138,804 previously unseen behavioral data samples, representing the weekly behavior of 11,567 players over a 12 week period. The results obtained were as follows:

●Number of games: 279

●Number of players: 11,657

●Control group sample collected from 8 different gambling operators in the Republic of Srpska

●Number of individual rounds/bets: 268,062,490

●Number of samples analyzed: 139,884

●Detected percentage of recreational players: 86.38%

●Detected percentage of players at-risk: 9.02%

●Detected percentage of problematic players: 4.61%.

Out of the 11,657 players, the model classified 4.61% as problematic gamblers, 9.02% as at-risk players, while the majority of players, 86.38%, were identified as recreational gamblers.

Online gambling datasets offer a valuable and rich resource for understanding problematic gambling and proposing interventions to mitigate the harmful impact of gambling in an online environment. Unlike most behavioral gambling studies, this research focuses on players who use their own funds to play games of their choice. It is evident that problematic gambling among such players is expressed through multiple behavioral indicators, including both monetary and non-monetary behavioral markers.

The challenge in this study was how to integrate data science results with existing clinical knowledge about the detailed characterization of behavior and cognitive processes in problematic gambling.

One of the advantages of this study is that it does not rely on players who resort to self-exclusion, as this may be less effective in identifying the harmful impact of gambling among players, some of whom may exhibit signs of problematic gambling or gambling addiction without even considering self-exclusion.

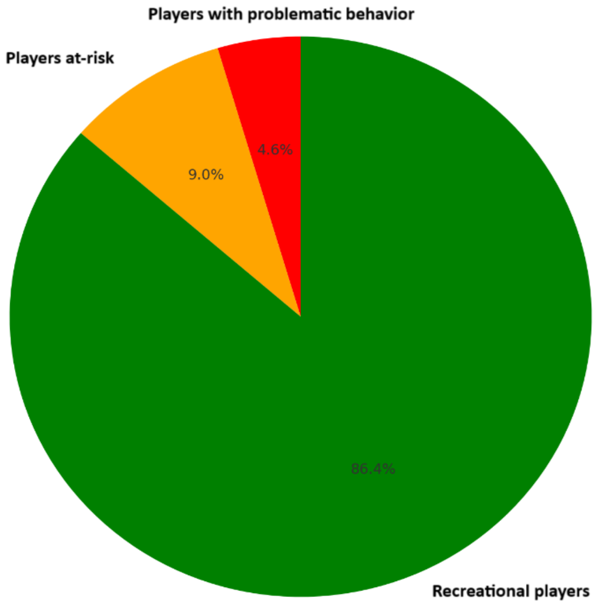

Figure 3. Classification of the control group of players using the trained model

Conclusion

There is an increasing need to develop effective strategies for preventing serious conditons caused by unhealthy lifestyle habits. Given the scope of this issue, personalized healthcare systems that apply innovative preventive strategies are becoming crucial. Previous research suggests that advances in machine learning enable the application of analytical methods in studying addictive behaviors. These innovations have the potential to revolutionize medical practice, particularly in terms of preventing and mitigating certain diseases. The quality of preventive care can be greatly enhanced as average users can better understand their health status and potential risks, while working closely with healthcare professionals.

When it comes to applying AI in healthcare, historical data on player behavior during gambling is essential for machine learning models that identify potentially problematic gambling. In this study, many harmful indicators were derived from behavioral variables that are independent of the financial weight of gambling. Although this study included a large sample and incorporated behavioral data from players who gambled with eight different operators in the Republic of Srpska, it still has certain limitations. If gambling operators were to share more data on actual player behavior, this would enable further research into responsible gambling and enhance algorithms for detecting problematic behavior. Factors such as player deposits, age, and frequency of contact with customer support could then be considered. Additionally, this study did not include sports betting, which is a very popular form of gambling in the Republic of Srpska.

The results of this study indicate that the application of machine learning algorithms, combined with psychiatric methods, can successfully identify behavioral patterns associated with recreational, at-risk, and problematic gambling. Based on the analysis of 11,657 players, 4.61% were classified as problematic gamblers, and 9.02% showed behaviors indicative of risk. These findings confirm that a significant portion of players fall into a risk zone even before developing full-blown gambling addiction, creating an opportunity for early intervention.

One of the key conclusions is that harmful behavioral patterns can be detected even when the financial aspect of gambling is not dominant, emphasizing the importance of including non-monetary behavioral indicators in predictive models. Furthermore, the study demonstrates that models can be trained on actual player behavior without relying on self-reporting mechanisms, such as self-exclusion, thereby increasing their practical applicability.

Based on these findings, several key recommendations are proposed to support the early detection of risky online gambling. One important approach involves incorporating a broad set of behavioral indicators, including bet variability, frequency of play, nightatime gambling activity, and shifts in gambling intensity. Another important recommendation is the use of machine learning algorithms to enable continuous monitoring and automatic classification of players according to their risk level. Personalized interventions should also be implemented, particularly for individuals identified as "at-risk", to prevent the development of addictive behaviors. Furthermore, closer collaboration between gambling operators and researchers is essential to improve access to larger datasets and to integrate additional variables such as demographic characteristics, interactions with customer support, and deposit histories. Lastly, educating players and introducing regulatory measures that require operators to apply responsible gambling tools based on behavioral analytics can further enhance efforts to mitigate gambling-related harm.

Future research should also include other forms of online gambling, such as sports betting, and compare behavioral patterns across jurisdictions and socioeconomic contexts. This would allow for further model optimization and improvement of global practices in gambling addiction prevention.

Machine learning is particularly well-suited for identifying behavioral patterns in problematic gamblers compared to recreational players. Gambling operators can provide "responsible gambling" tools to all users or target such interventions at specific player groups.

In future research, one of the objectives will be the specialized training of models for players from specific countries and comparing their performance. The reasoning is that previous studies have not provided statistics on the percentage of recreational, at-risk, and problematic players when comparing data from game providers whose online slots are played across multiple operators, spanning both regulated and unregulated markets, as well as countries with varying average net incomes and those located on different continents.

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BIHEVIORALNI OBRASCI U KOCKANJU PREKO INTERNETA IDENTIFIKOVANI POMOĆU VEŠTAČKE INTELIGENCIJE U KOMBINACIJI SA PSIHIJATRIJSKIM METODAMA

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Ovaj rad istražuje bihevioralne obrasce u kockanju preko interneta koristeći napredne tehnologije poput veštačke inteligencije, mašinskog učenja i koncepta Interneta ponašanja (engl. *Internet of Behaviour* – IoB). Digitalna revolucija je značajno olakšala pristup igrama na sreću dostupnim na internetu, što je dovelo do nastanka složenih obrazaca ponašanja igrača. Dok mnogi uživaju u kockanju kao obliku rekreacije, sve veća dostupnost igara na internetu može stvoriti rizike od razvijanja zavisnosti. Ključna je uloga veštačke inteligencije i mašinskog učenja u ranom prepoznavanju rizičnog ponašanja kod igrača. Algoritmi mogu analizirati podatke o igranju kako bi se identifikovali obrasci koji ukazuju na problematično ponašanje, uključujući preterano trošenje i „jurenje gubitaka”, tj. tendenciju da se nastavi kockanje ili da se poveća opklada u nastojanju da se gubici vrate. Pravovremene intervencije mogu pomoći u sprečavanju razvoja bolesti zavisnosti. Rad se posebno fokusira na upotrebu mašinskog učenja i neuronskih mreža (engl. *multilayer perceptron* – MLP) za identifikaciju različitih tipova igrača, analizirajući podatke o grupi igrača slot-igara dostupnih na internetu sa teritorije Republike Srpske. Pomoću iskustva iz kliničke prakse, modeli su trenirani na uzorku od 200 igrača i testirani na široj grupi sačinjenoj od 11.657 igrača kako bi predvideli rizično ponašanje u slot-igrama dostupnim na internetu. Pravci daljeg istraživanja predlažu implementaciju personalizovanih alata za kontrolu i podršku igračima. Pritom, akcenat se stavlja na promociju odgovornog kockanja i zaštitu javnog zdravlja. Rezultati su evaluirani na osnovu podataka igrača iz Republike Srpske, tržišta regulisanog zakonima koji štite igrače igara na sreću, i pokazuju kako regulisanje i edukacija mogu pomoći u smanjenju problema zavisnosti od kockanja.

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Ključne reči: *bihevioralni obrasci, Internet ponašanja, zavisnost od onlajn-igara, javno zdravlje, veštačka inteligencija*