Corrigendum to: Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning

AKADÉMIAI KIADÓ

Journal of Behavioral Addictions

13 (2024) 4, 901–903

DOI:
10.1556/2006.2024.30000

CORRIGENDUM

CORRIGENDUM TO: DEEP LEARNING(S) IN GAMING DISORDER THROUGH THE USER-AVATAR BOND: A LONGITUDINAL STUDY USING MACHINE LEARNING

VASILEIOS STAVROPOULOS[1,3], DANIEL ZARATE[1]*, MARIA PROKOFIEVA[2], NOIRIN VAN DE BERG[4], LEILA KARIMI[1], ANGELA GORMAN ALESI[5], MICHAELLA RICHARDS[6], SOULA BENNET[7] and MARK D. GRIFFITHS[8]

[1] Department of Psychology, Applied Health, School of Health and Biomedical Sciences, RMIT University, Australia

[2] Victoria University, Australia

[3] National and Kapodistrian University of Athens, Greece

[4] The Three Seas Psychology, Australia

[5] Catholic Care Victoria, Australia

[6] Mighty Serious, Australia

[7] Quantum Victoria, Australia

[8] International Gaming Research Unit, Psychology Department, Nottingham Trent University, UK

*Corresponding author.
E-mail: daniel.zarate.psychology@gmail.com

Published online: November 22, 2024

Journal of Behavioral Addictions, 12(4), 878–894. https://doi.org/10.1556/2006.2023.00062

The above paper should be modified as follows:

The tables provided in the original paper aligned with the analysis as it was initially described, with SMOTE applied prior to the data split. To solidify the results, the analysis has now been replicated with data balancing remedies, such as SMOTE, applied post-split, ensuring consistency and robustness in the findings.

Tables 6 and 9 should read as follows:

AKJournals

Table 6. Tuned algorithms performance on testing data (GD Wave 1)

	Null model	Random forests	Logistic regression	LASSO	Naïve Bayes	SVM Kernel	XGB	k-NN
ROC_AUC	0.500	0.707	0.645	0.665	0.573	0.524	0.637	0.661
PPV	0.500	0.808	0.796	0.796	0.806	0.796	0.816	0.800
NPV	N/A	0.500	N/A	N/A	0.300	N/A	0.400	0.333
F_meas	0.667	0.884	0.887	0.887	0.859	0.887	0.870	0.880
Specificity	0.000	0.934	0.566	0.896	0.802	0.953	0.896	0.981
Sensitivity	1.000	0.877	0.613	0.811	0.689	0.915	0.811	0.755
Recall	1.000	0.977	1.000	1.000	0.919	1.000	0.930	0.977
Accuracy	0.500	0.796	0.590	0.796	0.759	0.796	0.778	0.787

Accuracy reflects the ratio of correctly predicted cases, across the total number of cases. It is produced via the accumulation of the true positive and the true negative cases divided to the sum of all true positive, true negative, false positive and false negative cases. Accuracy values closer to 1 are considered desirable. Accuracy > 0.90= Excellent; 70%<Accuracy<90% = Very good; 60%<Accuracy<70% = Good; Accuracy<60% is poor (Allwiright, 2022). Area under the curve (AUC) refers to the area under the receiver operating characteristic (ROC) curve, as the latter is visualized in an orthogonal axis system/graph, where the horizontal line captures the false positive rate (FPR; 1 – specificity) and the vertical axis the sensitivity (True positive rate [TPR]; values closer to 1 are considered better/improved). AUC <0.5 = No discrimination; 0.5<AUC<0.7 = Poor discrimination; 0.7<AUC<0.8= Acceptable discrimination; 0.8<AUC<0.9 = Excellent discrimination; AUC>0.9 = Outstanding discrimination (Statology, 2021). Positive Predictive Value [PPV] or Precision is irrespective of the prevalence of a condition, and reflects the proportion/ratio of all the true positive classified cases divided by the addition of the true positive and the false positive cases (i.e., how many of those classified as positive were actually positive? Values closer to 1 are considered better/improved). Negative Predictive Value [NPV] is the ratio of participants truly diagnosed as negative, to all those who didn't meet the criteria for risk of disordered gaming. Specificity is the percentage of true negatives and Sensitivity is the percentage of true positives. Recall is associated to the prevalence of a condition and reflects the proportion/ratio of all the true positive classified cases divided by the sum of all the true positive and the false negative classified cases (i.e., how many of the true positive cases have been recalled? values closer to 1 are considered better/improved). F-Measure or F1-score/F-Score reflects the ratio of the multiplication of recall and precision, multiplied by two, and then divided by the accumulation of recall and precision, such that the balance between precision and recall achieved by the model is captured. Higher values are considered better/improved (Jiao & Du, 2016).

Table 9. Tuned algorithms performance on testing data (GD Wave 2)

	Null model	Random forests	Logistic regression	LASSO	Naïve Bayes	SVM Kernel	XGB	k-NN
ROC_AUC	0.5	0.613	0.704	0.500	0.624	0.560	0.500	0.587
PPV	0.5	0.786	0.797	0.797	0.829	0.797	0.797	0.797
NPV	N/A	0.000	N/A	N/A	0.278	N/A	N/A	N/A
F_meas	0.667	0.854	0.887	0.887	0.773	0.887	0.887	0.887
Specificity	0.000	0.000	0.000	0.000	0.417	0.000	0.000	0.000
Sensitivity	1.000	0.936	1.000	1.000	0.723	1.000	1.000	1.000
Recall	1.000	0.936	1.000	1.000	0.723	1.000	1.000	1.000
Accuracy	0.500	0.746	0.590	0.797	0.661	0.797	0.797	0.797

Accuracy reflects the ratio of correctly predicted cases, across the total number of cases. It is produced via the accumulation of the true positive and the true negative cases divided to the sum of all true positive, true negative, false positive and false negative cases. Accuracy values closer to 1 are considered desirable. Accuracy > 0.90= Excellent; 70%<Accuracy<90% = Very good; 60%<Accuracy<70% = Good; Accuracy<60% is poor (Allwright, 2022). Area under the curve (AUC) refers to the area under the receiver operating characteristic (ROC) curve, as the latter is visualized in an orthogonal axis system/graph, where the horizontal line captures the false positive rate (FPR; 1 – specificity) and the vertical axis the sensitivity (True positive rate [TPR]; values closer to 1 are considered better/improved). AUC <0.5 = No discrimination; 0.5<AUC<0.7 = Poor discrimination; 0.7<AUC<0.8= Acceptable discrimination; 0.8<AUC<0.9 = Excellent discrimination; AUC>0.9 = Outstanding discrimination (Statology, 2021). Positive Predictive Value [PPV] or Precision is irrespective of the prevalence of a condition, and reflects the proportion/ratio of all the true positive classified cases divided by the addition of the true positive and the false positive cases (i.e., how many of those classified as positive were actually positive? Values closer to 1 are considered better/improved). Recall or sensitivity is associated to the prevalence of a condition and reflects the proportion/ratio of all the true positive classified cases divided by the sum of all the true positive and the false negative classified cases (i.e., how many of the true positive cases have been recalled? values closer to 1 are considered better/improved). Negative Predictive Value [NPV] is the ratio of participants truly diagnosed as negative, to all those who didn't meet the criteria for risk of disordered gaming. Specificity is the percentage of true negatives and Sensitivity is the percentage of true positives. F-Measure or F1-score/F-Score reflects the ratio of the multiplication of recall and precision, multiplied by two, and then divided by the accumulation of recall and precision, such that the balance between precision and recall achieved by the model is captured. Higher values are considered better/improved (Jiao & Du, 2016).

Details about the corrections can be found in Stavropoulos, et al. (2024)

The authors.

REFERENCES

Stavropoulos, V., Prokofieva, M., Zarate, D., Colder Carras, M., Ratan, R., Kowert, R., … Griffiths, M. D. (2024). Machine learning(s) in gaming disorder through the user-avatar bond: A step towards conceptual and methodological clarity. Reply to: User-avatar bond as diagnostic indicator for gaming disorder: A word on the side of caution. *Journal of Behavioral Addictions* (advanced online publication.) https://doi.org/10.1556/2006.2024.00063.