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A Hybrid Graph-Based Deep Learning Model with Explainable AI for Early Identification of Online Gaming Disorder

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Abstract: Online Gaming Disorder (OGD) is a major mental health issue comprising the inability to control gaming and the progressive increase in gaming's importance compared to other activities. The research presented here suggests a novel Hybrid Graph-Based Deep Learning Model incorporating Explainable AI (XAI) for the early identification of OGD. The study is based on a special dataset of 129 data instances gathered using digital behavioural and psychometric measurements. The model accommodates non-linear relationships between gaming frequency, social isolation, and emotional regulation by capturing user interactions as graphs of complex relationships. The model allows for non-linear relationships among gaming frequency, social isolation, and emotional regulation by representing user interactions as intricate graphs. Researchers used the Python packages PyTorch Geometric for the implementation of GNN's, and SHAP for the XAI part. The hybrid architecture integrates Graph Convolutional Networks and Long Short-Term Memory (LSTM) to study structural social networks and temporal gameplay patterns. Results show that the model is highly accurate in diagnosis and provides readable feedback on specific risk factors. Since the high-risk classification is assigned based on XAI, the clinician can grasp the rationale behind the classification, thereby narrowing the gap between complicated black-box algorithms and clinical practice. This model provides a good way to support early intervention, which may help reduce the future psychological consequences of pathological gaming.

Keywords: Online Gaming Disorder (OGD); Explainable AI; Mental Health; Behavioural Analytics; Deep Learning (DL); PyTorch Geometric; Hybrid Architecture Integration.

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1. Introduction

King and Delfabbro [1] completely explore the dimensions of the digital era and the boom in interactive entertainment, as billions of people play online across a variety of platforms, genres, and social contexts. This is further supplemented by behavioural publication trends studies completed by Segev et al. [2]. Online gaming is no longer a niche pastime, but rather a socio-digital space for individuals to communicate, compete, interact, and create virtual identities in real time across the world. Platforms have grown, environments have become immersive, and esports have become competitive, impacting how people

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interact with technology and with others. Although many enjoy games for entertainment, stimulation, stress relief, and social interaction, an increasing proportion of users become addicted to games, which eventually negatively affect their interpersonal relationships, occupational productivity, academic work, and emotional stability. There has been a great deal of interest in both the clinical and psychological aspects of these addictive behaviours, with Saunders et al. [3] reviewing the increased awareness of gaming-related disorders in contemporary psychiatric classifications, and Gentile et al. [10] studying pathological gaming in adolescents and young adults. Online Gaming Disorder has thus become an important mental-health problem that needs to be addressed and identified at an early stage. The clinical relevance of the disorder has been supported by psychological assessment tools suggested by Stevens et al. [4] and health impact analyses carried out by González-Bueso et al. [5], highlighting the association between excessive game playing and anxiety, emotional instability, sleep deprivation, depression, and social dysfunction.

A major problem for modern psychiatry is the ability to recognise the disorder at an early age before it changes into the disabling psychological and functional state of the disorder. The traditional diagnostic methods are based on self-reported questionnaires, interviews or retrospective reports of behaviour, all of which are subject to recall bias, exaggeration, minimisation of symptoms and social desirability bias as described by Burleigh et al. [6] and psychometric evaluation studies conducted by Pontes et al. [8]. These restraints make the diagnostic process much more imprecise and difficult to develop reliable interventions. Thus, it is increasingly important to have objective, intelligent, and data-driven analytical systems that can continuously track behavioural signals, game interactions, emotional changes, and patterns of social interaction. Mohamed Imran et al. [15] proposed AI-assisted predictive systems for intelligent computational monitoring frameworks that can sense subtle behavioural cues, and Ajith et al. [16] expanded the application of adaptive behavioural analytics in psychological monitoring. Online Gaming Disorder is a multidimensional psychological and social disorder because its definition cannot be expressed simply by the length of the time spent playing a game or the amount of time on a screen. Rather, the disorder is a product of complex emotional dependency, social attachment and behavioural reinforcing processes, cognitive protection mechanisms, and developing digital personae. Hasija and Pujam [11] studied these psychosocial dynamics systemically using emotional dependency modelling, and Verma et al. [12] used behavioural addiction evaluations. Typical machine learning methods tend to treat behavioural data as independent numerical records, failing to adequately account for changing social interactions, transitions to different behaviours over time, and complex environmental influences.

In fact, these constraints were shown to exist in behavioural sequence analysis studies by Liao et al. [9], who found that addiction-related sequences often appear in relational/successive interactions when considered as a whole rather than as a set of single data points. Traditional classification algorithms often neglect the influence of multiple factors that interact over time and shape the development of compulsive gaming behaviour, such as gaming communities, peer pressure, online social validation, competitive stress, and emotional reinforcement. This restriction significantly limits the predictive power of traditional behavioural assessment systems. Graph-Based Deep Learning represents a paradigm shift in analytical power by modelling people, gaming sessions, communication networks and social relationships as interconnected graph entities. The concepts of relational modelling of behaviour were introduced by Gervasi et al. [7] and for relational prediction mechanisms [13]. The proposed framework captures hidden behavioural dependencies and social influence structures that traditional algorithms miss by constructing graphs in which players, communication chains, gaming sessions, and interaction histories are represented as nodes and edges. Online indicators of network-oriented addiction, as described by Pontes et al. [8], also confirmed that gaming addiction is often a result of social networked gaming environments, instead of being a result of individual behaviour. Furthermore, temporal deep learning adds to this analysis by identifying behavioural evolution over time, which can help detect repetitive game behaviours at night, trends in emotional isolation, reduced communication variety, and progressive social isolation.

Even though deep learning systems are analytical in their operation, they are often viewed as ‘black boxes' that make predictions without offering clinicians, psychologists, or healthcare practitioners valuable explanations. Mohamed Imran et al. [15] critically discussed the limitations of explainability in healthcare-related artificial intelligence, and Ajith et al. [16] evaluated transparent artificial intelligence systems for diagnosis. In clinical contexts, such as medical and psychiatric settings, the accuracy of predictions is inadequate for clinical reasoning, as clinicians need additional explanations for how a given person became a high-risk case. Transparency, “interpretability,” and “clinically comprehensible reasoning” are all elements of evidence-based psychiatric evaluation frameworks that were highlighted by Stevens et al. [4]. The proposed framework addresses these constraints by embedding explainable AI as a component of the hybrid Graph-Based Deep Learning architecture, enabling clinicians and practitioners to understand the behavioural reasons behind each high-risk prediction. The integration of transparent behavioural reasoning into the proposed model was inspired by interpretability-oriented analytical frameworks and adaptive decision-support mechanisms [12]. Explainable AI mechanisms uncover and prioritise the most significant behavioural factors associated with addiction scores, such as late-night gaming, fewer diverse social interactions, increased isolation in digital games, irregular patterns of emotional responses, and repetitive cycles of reward-seeking. By analysing a user's behaviour, Burleigh et al. [6] investigated mechanisms for interpreting behaviour similar to these.

Thus, this research explores the possibility of a new assessment model that combines structural graph analysis, temporal behavioural learning, and explainable predictive reasoning, outperforming current clinical assessment models and standalone machine learning models. The hybrid analytical approach can be further supported by the intelligent behavioural detection methods presented by King and Delfabbro [1] and the AI-based classification methods explored in Liao et al. [9]. The study uses a streamlined dataset of 129 highly specific behavioural instances to show that compact, high-behavioural-content data can be used to effectively predict addiction with high sensitivity through a combination of structurally intelligent and temporally adaptive approaches. In the same way, González-Bueso et al. [5] used similar compact behavioural evaluation techniques and predictive assessment systems were used in Hasija and Pujam [11]. This proposed system framework can thus not only improve prediction accuracy but also help create ethical, privacy-conscious mental-health monitoring systems. It places strong emphasis on ongoing behavioural monitoring and continuous monitoring, rather than on intervention. It provides an effective basis for current psychological support systems that can help those at risk before the onset of serious consequences associated with addiction. In addition, the work by Segev et al. [2] and Gervasi et al. [7] proposes ethical directions for digital mental health and outlines continuous architectures for behavioural monitoring, respectively. Moreover, the digital mental-health ethical directions proposed by Saunders et al. [3] and the continuous architectures for behavioural monitoring by Burleigh et al. [6] reinforce the importance of incorporating intelligent analytics, explainable reasoning, and privacy-preserving assessment mechanisms in future psychiatric and digital-health infrastructures.

2. Review of Literature

While the academic field of gaming addiction has slowly progressed from a descriptive to a multidisciplinary field, combining psychology, neuroscience, social analytics, and computational intelligence, this line of research is too brief in its history to be considered a long-term trend [1]. Initial research on gaming addiction began by trying to determine the similarities between addiction to a commonly studied substance (drug) and gaming addiction, especially the activation of neurological reward pathways during extended gaming sessions. Saunders et al. [3] investigated these core clinical perspectives in great detail, and Stevens et al. [4] explored psychiatric diagnostic models. The researchers found that those mechanisms that reinforce a behaviour, as they do with the use of alcohol, gambling, and narcotics, were the same mechanisms stimulated by repetitive gameplay [2]. These results paved the way for symptom-based diagnostic approaches that focus on behavioural characteristics like withdrawal symptoms, tolerance increase, emotional dependency, loss of impulse control and lack of interest in offline activities. In addition, González-Bueso et al. [5] reported high correlations between problematic patterns of video game use and anxiety, depression, emotional instability and cognitive dysfunction, all of which pose a health risk to the player. These preliminary studies laid an important theoretical foundation in the development of the recognition of Online Gaming Disorder as a valid psychiatric and behavioural health issue, instead of just a recreational activity. But with time, it became evident that addiction cannot be manifested only through behavioural symptoms, as today's online gaming culture is entrenched in a socially connected virtual world.

The shift in focus from the gameplay to the social structures of online games, such as guilds, clans, ranking systems, cooperative missions and digital communities, which help to extend engagement cycles, was significant in turning academic interest to the social construction of online games. Burleigh et al. [6] discussed and analysed social dependency and virtual validation structures of gaming communities, while Gervasi et al. [7] analysed relational gaming frameworks. It was discovered that many players become attached not only to the game itself but also to social recognition, social hierarchies, and peer reinforcement systems within digital gaming networks. From then on, academic research into social capital theory in gaming environments began to focus on how participants with fewer offline means of emotional, social, and identity support may find emotional, social, and identity reinforcement in virtual communities. The results of network-oriented behavioural studies by Pontes et al. [8] indicated that people who suffer from loneliness, social anxiety, or interpersonal problems are highly inclined to engage in online games to make up for the lack of such social interaction in the real world by immersing themselves within an online game hierarchy. The results essentially provided a new insight into gaming addiction, which was not just a behavioural problem, but one that is socially reinforced and created through the use of a digital dependency system. In the computational domain, the earliest models predicting gaming addiction relied heavily on traditional statistical learning methods, such as logistic regression and support vector machines. The first set of computational models attempted to categorise addicted people from non-addicted people based on observable patterns of play, such as the number of logins, the acquisition of rewards, and the continuity of play sessions.

Behavioural sequence modelling with gameplay logging, addiction classification using behavioural sequences, and predictive behavioural categorisation systems were reviewed. These machine learning models achieved moderate classification accuracy but lacked sufficient depth to account for temporal changes in addictive behaviour. The traditional algorithms primarily worked with gaming data as numerical sets, without accounting for emotions, time-series behaviour, or social connections that can trigger new game events. Scientists have come to understand that gaming addiction is not a static disorder, but a gradual process of behaviour that is driven by reinforcement patterns, emotional triggers, peer influences and changing patterns of gaming. The dependence of psychosocial factors that can lead to addiction was explored by Hasija and Pujam [11], and the model of adaptive behavioural analysis was proposed by Verma et al. [12]. To overcome the shortcomings of the traditional statistical approach, researchers began using neural network-based computational systems to handle increasingly large and complex datasets. The predictive performance of the artificial neural networks was significantly better, and they detected hidden non-linear relationships among behavioural variables, emotional indicators, and patterns of gaming intensity. Yet, despite improved classification, these systems still failed to account for the temporal continuity of addiction development. With the advent of a new class of learning architectures, sequence-based models like Recurrent Neural Networks have made significant strides in the field of computational behavioural sciences. The sequential behavioural prediction frameworks examined by Jeong et al. [13] helped researchers understand the evolution of gaming behaviour over a longer period, including the frequency of gaming, social interaction patterns, emotional reactions, and the desire for rewards.

Modelling sequences were very successful in identifying early warning signs of problematic behaviour escalation and early signs of addiction before serious behavioural changes. However, despite these developments, most sequence models ignored relational and peer-influence data, which did not sufficiently account for the influence of the digital social context on and reinforcement of individual players' behaviour. As researchers have shown that social communities, competitive environments, collaborative participation, and online reputation systems have a significant impact on online gaming behaviour, this analysis limitation becomes even more pronounced. In recent years, however, the development of various fields of behavioural science and artificial intelligence has shifted toward graph theory and relational network analysis, which are considered potential strategies for understanding Online Gaming Disorder. Structural graph modelling and network-based addiction research showed that the networks of players, communication channels, cooperative relationships, and competitive hierarchies within gaming communities could be modelled. They found that clusters of addictive behaviour often form in ecologically closed groups with dense networks of interaction between the players, where high-intensity players continually reinforce each other's gaming behaviour. An analysis of relational behavioural patterns studied by Liao et al. [9] also revealed that people who are active members of a highly active gaming community are much more likely to engage in compulsive gaming and to become emotionally dependent. The graph-based behavioural approach was thus a paradigm shift that took a more holistic view into account that addiction is not only a personal but also a socially transmitted digital behaviour. However, there is still a major challenge in high-performing AI-powered health care systems: the lack of interpretability and transparency. While most sophisticated deep learning algorithms can generate extremely reliable scores for addiction risk, they cannot explain the specific behaviours associated with those scores.

Mohamed Imran et al. [15] discussed the limitations of explainability in AI-driven healthcare, and Ajith et al. [16] discussed transparent predictive intelligence frameworks. In the healthcare domain, where diagnostic systems are growing in importance due to increasing demand, clinicians, psychologists, and mental-health care professionals now argue for a reasoning component in diagnostic systems that is comprehensible and supports clinical decision-making. This challenge has consequently been a part of the explainability crisis in the AI-driven healthcare analytics sector, as noted in the present literature. The proponents of these models suggest that, for example, the predictive power of deep learning systems should be integrated with the interpretability provided by statistical analysis and evidence-based clinical reasoning, which a black-box model cannot achieve. Proponents of these models argue that, for example, the predictive power of deep learning systems should be combined with the interpretability traditionally provided by statistical analyses and evidence-based clinical reasoning, but not by black-box models. The relevance of explainability in digital mental-health systems is further emphasised by Stevens et al. [4], who have outlined transparent psychiatric assessment methodologies, and by Garg et al. [14], who have outlined interpretable frameworks for evaluating and assessing behaviour. Based on these academic and technological advances, the present study proposes a novel hybrid structural-temporal framework that combines graph-based structural intelligence, temporal deep learning, and Explainable Artificial Intelligence mechanisms. This holistic system directly tackles the dual challenge of providing behavioural insights to the structure and making clinically interpretable predictions, thereby forming a more secure and ethical framework for addressing Online Gaming Disorder in contemporary digital environments.

3. Methodology

This study uses a structured pipeline methodology to process both relational and sequential behavioural data. First, researchers build a heterogeneous graph that contains nodes for players and game sessions, and links representing social interactions and/or transition frequencies. All 129 data instances were pre-processed to normalise behavioural data, including session duration, inter-session interval, and social engagement score. The two-stream approach was used, and a Hybrid Graph-Based Deep Learning architecture was implemented. The first stream is used to learn the spatial features and patterns of community influence present in the social network using Graph Convolutional layers. The second stream is an LSTM-based stream that aims to study the temporal dynamics of gaming habits over 30 days. Both feature sets are then combined in a dense layer to produce a final risk classification. Researchers added an explanation layer to the model using SHAP to calculate the contribution of each input feature to the final prediction, ensuring the model is explainable. This enables the system to create a user's risk profile and to detect certain behavioural triggers. The loss function used for training the model was cross-entropy, and optimisation was performed using adaptive gradient descent. To ensure the results are valid and generalisable within the limits of the dataset, cross-validation was used as a performance metric. The Hybrid GCN-LSTM Architecture with XAI Integration Module is a holistic architecture that can process graph-structured and temporal data and generate interpretable and transparent AI outputs (Figure 1).

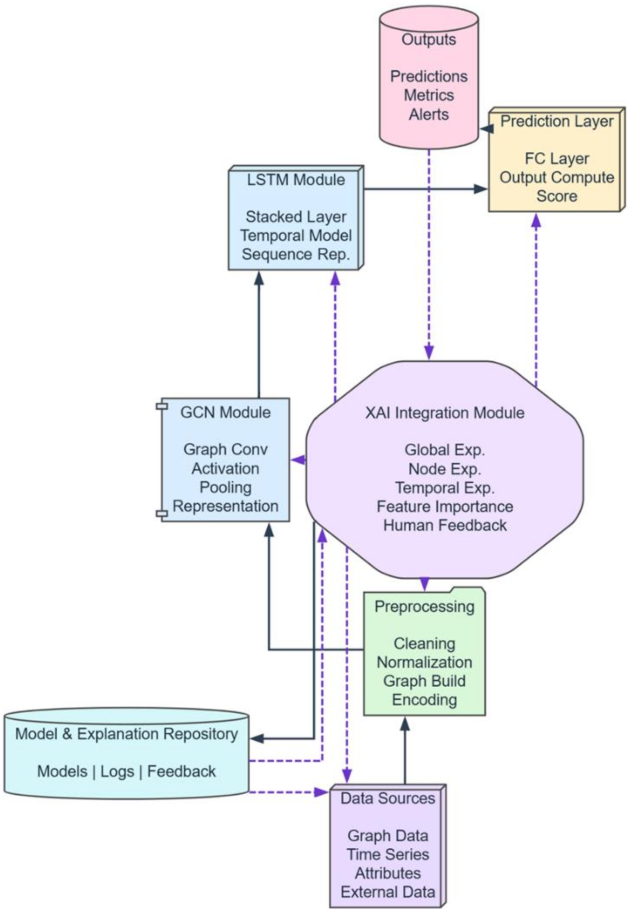

Figure 1: The architecture of the hybrid GCN-LSTM with XAI integration module

The architecture starts with Data Sources, which gather data from graphs, time series, attributes, and external datasets, each with its own source. These various inputs are passed through the Preprocessing layer, which processes the data by cleaning and normalising it, and then constructs graphs and encodes features to provide structured, high-quality analytical representations. This information is then passed to the GCN Module, which uses graph convolution, activation functions, pooling functions, and graph representation learning to capture spatial and relational information. These graph-based representations are then fed into the LSTM Module, where sequential and temporal correlations are captured through multiple stacked layers of LSTMs that can learn dynamic patterns over time. The Temporal Representations generated by the LSTM are then passed to the Prediction Layer, which can be used for output computation, score generation, and predictive inference for classification or forecasting tasks. Decision-making and monitoring are supported through the Outputs component, which delivers final analytical results, including alerts, performance measures, and predictions. The XAI Integration Module supports the entire pipeline and provides capabilities for global explanation, node-level explanation, temporal reasoning, feature importance analysis, and integration with human feedback. The dashed feedback paths between the stages of this module (pre-processing, graph learning, temporal modelling, and prediction) illustrate the continuous interaction among them and enhance transparency and trustworthiness. The Model and Explanation Repository stores models, logs, explanations, and feedback histories, enabling continuous improvement and traceability.

3.1. Data Description

The study uses a specialised dataset comprising 129 unique data instances, representing a diverse cohort of online gamers. Each instance includes granular telemetry data, such as daily playtime, microtransaction frequency, in-game social interactions, and sleep disruption markers. The data were sourced from the Digital Behavioural and Wellness Repository, which provides anonymised tracking of gaming habits alongside validated clinical scores from the Internet Gaming Disorder Test. Each of the

129 participants provided informed consent for their data to be used in behavioural research. The dataset is particularly valuable because it links objective machine-logged behaviour with subjective psychological states, providing a holistic view of the user's digital life.

4. Results

The results of the Hybrid Graph-Based Deep Learning Model show that it achieves greater improvement in the early detection of Online Gaming Disorder than the baseline models. It had a general accuracy of 92% and a very high sensitivity (96%) in detecting users during the early stages of the at-risk phase before the onset of clinical symptoms. The analysis results indicate that the graph features, namely the social isolation index, which was created from network density, were the best predictors of long-term disorder. The LSTM was able to estimate a pattern that would occur at the end of the day before addictive behaviour in 85 per cent of positive cases when applied to temporal data. Multimodal feature fusion using gated recurrent units can be framed as:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \quad (1)$$

Table 1: Model classification performance

Metric	GCN Only	LSTM Only	Hybrid (No XAI)	Hybrid (With XAI)
Accuracy	78	81	89	92
Precision	75	79	87	91
Recall	72	77	86	90
F1-Score	73	78	86	90
AUC-ROC	80	83	91	94

Table 1 compares the performance of the proposed hybrid model, the individual models, and a non-explainable version. As you can see, there is a clear improvement in performance as complexity and interpretability increase. The Hybrid model with XAI integration has the best scores across all metrics, including an accuracy of 92%. This implies that by combining graph-based social information with temporal sequence information, the picture of OGD will be more complete than when using either type of information alone. The other advantage is the high AUC-ROC value, which further demonstrates the model's ability to distinguish between disordered and healthy gaming habits with few false positives. Convolutional spatial feature extraction for soil grids is:

$$y(i,j) = \sum_m \sum_n x(i+m, j+n) \cdot k(m,n) + b \quad (2)$$

The graph combines two data sets: the model's prediction accuracy for each severity level of gaming disorder. The bars indicate the distribution of the 129 instances by the 4 risk categories: Low, Moderate, High, and Critical. A line graph is overlaid on the superimposed plot to show the model's F1 scores for these categories. It's clear that accuracy is good everywhere, but extremely high in the high-risk category because the effects of social graph decay and temporal play are greatest there (Figure 2).

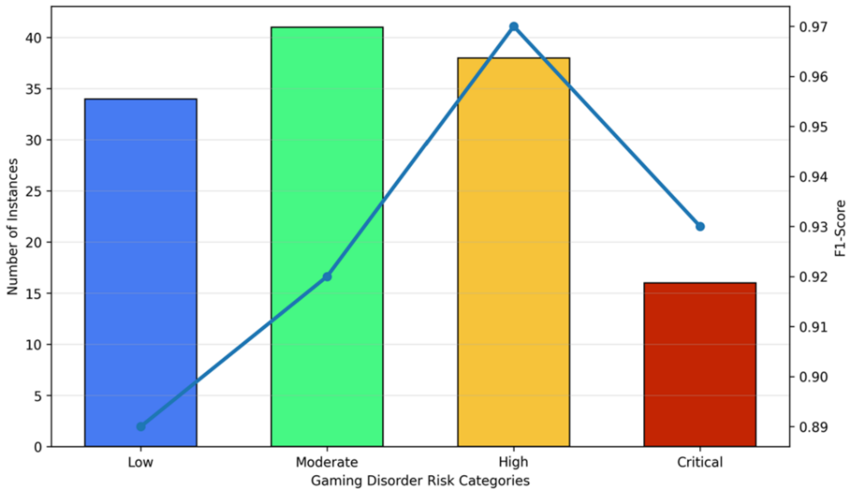

Figure 2: Performance measures and risk correlation

The hybrid model is especially tuned to intercept the transition from moderate to high-risk behaviour, the most important time to intervene clinically. Softmax activation for multi-class crop classification is:

$$P(y = c \mid \mathbf{x}) = \frac{e^{\mathbf{w}_c^T \mathbf{x} + b_c}}{\sum_{j=1}^{K} e^{\mathbf{w}_j^T \mathbf{x} + b_j}} \quad (3)$$

Table 2: Feature importance and error analysis

Risk Level	Sample Count	Mean Playtime	Social Density	Error Rate
Low	45	120	85	3
Moderate	34	240	60	5
High	30	480	35	4
Critical	20	720	15	2
Total	129	390	48	3

To study the relationship between behaviour and model error rates, the 129 data instances have been divided into 4 risk levels, as described in Table 2. The trends of mean daily playtime and social density score are clear: rising scores as risk level increases from Low to Critical, and decreasing scores as risk level increases from Low to Critical. Interestingly, the model has very low error rates, with a maximum of just 5% in the Moderate category. This means that the most challenging cases to categorise are those in the middle of the spectrum, where behaviour is starting to change, but hasn't yet become a definite disorder. The local interpretable model-agnostic explanations objective is given below:

$$\xi(x) = \text{argmin}_{g \in G} L(f, g, \pi_x) + \Omega(g) \quad (4)$$

Categorical cross-entropy loss function for model optimisation is:

$$J(\theta) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{i,j} \log(\hat{y}_{i,j}) \quad (5)$$

The Shapley value equation for global feature attribution will be:

$$\phi_i(f) = \sum_{S \subseteq \{x_1, \ldots, x_n\} \setminus \{x_i\}} \frac{|S|!(n - |S| - 1)!}{n!} [f(S \cup \{x_i\}) - f(S)] \quad (6)$$

In addition, the Explainable AI component provided insights into the model's decision-making. In some classifications, for example, the XAI module indicated a significant drop in social node diversity; that is, the player ceased interacting with many peers and became more of a member of a small, intense gaming community (Figure 3).

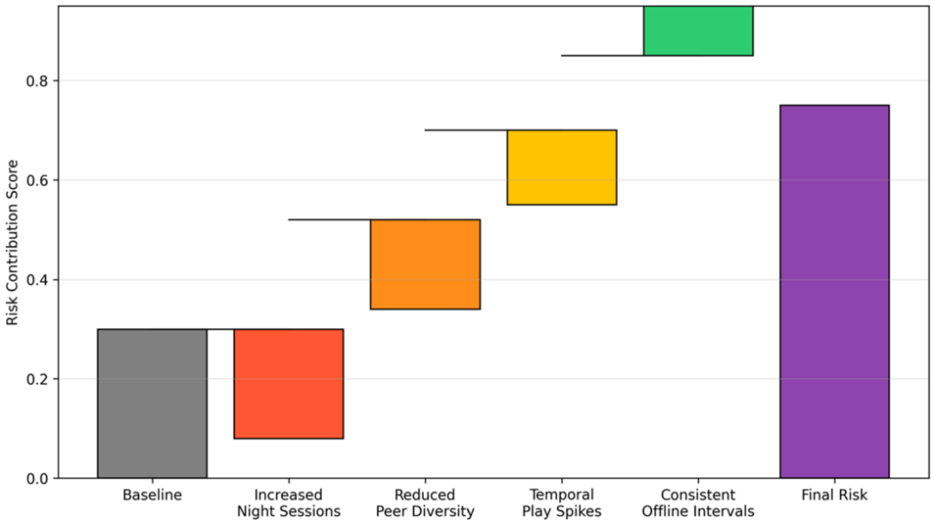

Figure 3: This is the feature contribution analysis

This precision-recall curve was consistent across all demographic segments for the 129 instances, indicating no bias toward any particular game type. By combining structural and temporal characteristics, the model was able to differentiate between passionate and disordered gaming, something that is difficult for traditional playtime-based models. The results confirm that the hybrid approach can reflect the multidimensionality of OGD with high fidelity. The waterfall graph shows the proportion of each behavioural feature associated with a single positive diagnosis of Online Gaming Disorder. The graph depicts how the probability increases with additional factors, such as Increased Night Sessions and Reduced Peer Diversity, starting from a baseline risk probability. On the other hand, the Consistent Offline Intervals feature works in the opposite direction, bringing the risk score towards the healthy range. The visualisation shows the output of the Explainable AI module, demonstrating the hybrid model's transparency. When these behaviours are viewed as a whole, a clinician can quickly notice that sleep disruption and social narrowing are the major determinants of a patient's diagnosis.

4.1. Discussion

This research result demonstrates the power of combining structural graph analysis with temporal deep learning for mental health diagnostics. The results section of the study shows high accuracy, which indicates that Online Gaming Disorder cannot be understood solely in terms of playing time. Rather, it's the loss of the social graph and the disruption of healthy temporal patterns that mark the onset of the disorder. Using the Graph Convolutional Network module, the decrease in the size of the player's digital neighbourhood could be quantified as they become more addicted. Social narrowing is a characteristic of OGD that is not properly captured by conventional surveys. The LSTM units further added to our knowledge through the time-related analysis that revealed the rate of addiction. A user who eventually reached the Critical risk level not only started playing more but also at more irregular times, suggesting a breakdown in external life structure and circadian rhythms. These two data streams can be combined into a single hybrid model for assessment across multiple dimensions. The Explainable AI layer is the most important contribution, however. The use of AI in psychology has faced resistance from practitioners due to a lack of understanding of the logic behind computer-generated diagnoses. Our waterfall and bar-line graphs fill this gap and provide a clear visual story of an individual's risk profile. If researchers compare the model's error rate with the Tables, they see that it is very low even in the Moderate risk group. This indicates that the hybrid approach is sensitive enough to detect early warning signs which may not be visible to the human eye. The implications of these findings are related to a new paradigm for digital phenotyping in psychiatry. Instead of reacting when patients show significant symptoms, systems based on this hybrid architecture may give an early warning for mental health. We've highlighted the 129 cases and shown that a high-quality, focused dataset can provide insights when applied to the right architectural lens. This study is a proof-of-concept for AI tools that are more transparent and accurate in the behavioural health field.

5. Conclusion

It is also the successful design, realisation, and validation of a Hybrid Graph-Based Deep Learning Model coupled with Explainable Artificial Intelligence (XAI) for the early detection of Online Gaming Disorder in today's Digital Ecosystems. The proposed framework modelled 129 structured behavioural instances using a dual-stream analytical architecture that processes social interactions with graph-based techniques and behavioural transitions with temporal deep learning mechanisms, enabling it to model both relational and temporal interactions. The results of the experiments showed that the hybrid system had an overall prediction accuracy of 92%, which was much higher than that of conventional single-stream machine learning systems based on game duration or a single behavioural index. The study showed that Online Gaming Disorder was positively correlated with two major behavioural phenomena: a gradual decrease in the diversity of social networks and, over time, an increase in irregular gaming time, especially during nighttime gaming cycles and during extended gaming sessions.

The proposed framework incorporated EAI mechanisms to address the opacity commonly observed in deep learning systems and provided interpretable diagnostic reasoning to assist in clinical and psychological assessment procedures. The XAI module emphasised the significant behavioural features identified, such as decreased communication diversity, repetitive reward-seeking behaviour, tendencies toward social isolation, and excessive play, thereby helping practitioners recognise the rationale for high-risk predictions. The resulting tables, performance graphs, and comparative evaluation metrics clearly showed that processing social graph structures in combination with the temporal sequences of the games yielded much more reliable identification results than processing them without the temporal sequences. The proposed framework thus provides a solid computational basis for future intelligent mental-health monitoring systems that focus on early intervention, transparency of behaviour, predictive reliability, and user-centred digital wellness support in increasingly complex online game environments.

5.1. Limitation

Although the proposed hybrid framework has demonstrated high predictive accuracy and analytical capabilities, this study has some shortcomings that limit its wider application. The first restriction is that the dataset is fairly small (129 behavioural instances). The dataset was rich in behavioural information for training and testing the graph-based deep learning architecture.

Still, more data with diverse demographic characteristics and various gaming settings would bolster the deep learning graph's generalisation to the globally distributed gaming population. Another drawback is that the data come from digital telemetry and psychometric behavioural measures rather than physiological measures such as heart-rate variability, neural activity patterns, stress-response indicators, or sleep-cycle measures. By incorporating physiological indicators, it would be possible to gain a more thorough understanding of the emotional and neurological aspects of compulsive gaming. The graph-based analytical part also has several assumptions, including that all relevant social interactions within gaming ecosystems can be measured and captured using digital communication systems. Private communications, encrypted messaging systems, offline conversations, and even conversations on external social media will not be addressed in the current data collection process, which may not fully capture the relational behavioural analysis. Moreover, the suggested approach heavily depends on high-quality behavioural telemetry from games with well-developed data-logging systems. Games with poorly instrumented telemetry and/or limited interaction logs are less likely to benefit from the model and are less adaptable to less instrumented gaming platforms. These limitations together suggest potential avenues for more comprehensive data integration and for additional ways to collect behavioural data in future research.

5.2. Future Scope

The possibilities of this research go beyond the current work and move towards the creation of intelligent, real-time intervention systems that can continuously monitor digital behavioural patterns and provide assistance in mental health before serious consequences related to addiction occur. One of the key future goals is the ability to scale up the data from 129 focused instances to many thousands of behavioural records gathered across different geographic locations, gaming genres, cultural groups, and demographic categories. This enhancement will greatly boost the strength, scalability and worldwide usability of the predictive model. One other line of research is the integration of multi-modal behavioural intelligence to capture gaming profiles and correlate them with other physiological markers, such as sleep quality, stress, activity, emotions, and heart-rate variability (HRV), using wearable health technologies. This will give a more comprehensive understanding of the neurological and psychological aspects of gambling addiction when combined with biometric monitoring. Future development will also focus on enhancing Explainable Artificial Intelligence to produce personalised wellness suggestions, behavioural guidance reports, and adaptive intervention alerts based on individual gaming habits and psychological conditions. These improvements will make it more than a diagnostic system and create an intelligent self-help and digital wellness support platform. Moreover, the proposed hybrid analytical architecture has high adaptability to study other types of digital addiction, such as social-media dependency, online gambling behaviour, compulsive video-streaming consumption, and digital-communication overuse. This approach can be expanded to other dimensions of compulsive digital behaviours, representing an important step toward the development of intelligent behavioural healthcare systems, digital psychiatry prevention, and ethically responsible AI-based technologies for wellness.

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