Artificial Intelligence as a Predictive Tool in Drug Addiction: A Comprehensive Review

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Artificial Intelligence as a Predictive Tool in Drug Addiction: A Comprehensive Review

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Abstract:

Drug addiction is a complex disorder where both genetic and environmental factors play a significant role in its development. Although the clinical evaluation is the predominant diagnostic approach for the drug addiction, this method is considered a time-consuming and relies on human observation alongside specialized equipment and tools. Barriers such as stigma and financial constraints can also limit patient access to medical facilities. Advanced technologies like artificial intelligence (AI) can significantly enhance the practical evaluation, diagnosis of drug addiction and accurately guide the clinical situation. AI can play crucial role by personalizing the treatment by analyzing vast amount of data from the patient, early detection of abuse or relapsing, monitoring patient behavior and prediction individuals at high risk of developing addiction. This review exhibits studies that use artificial intelligence and deep learning architecture in various areas to predict these drugs, their abuse, and their metabolism with the known features, providing a framework for guiding future studies.

Keywords: Artificial intelligence, Deep learning, Drug addiction.

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الذكاء الاصطناعي كأداة تنبؤية في إدمان المخدرات: مراجعة شاملة

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المستخلص:

إدمان المخدرات هو اضطراب معقد حيث تلعب العوامل الوراثية والبيئية دورًا كبيرًا في تطوره. على الرغم من أن التقييم السريري هو النهج التشخيصي السائد لإدمان المخدرات، إلا أن هذه الطريقة تعتبر مستهلكة للوقت وتعتمد على الملاحظة البشرية إلى جانب المعدات والأدوات المتخصصة. يمكن أن تحد العوائق مثل وصمة العار والقيود المالية من وصول المرضى إلى المرافق الطبية. يمكن للتكنولوجيا المتقدمة مثل الذكاء الاصطناعي (AI) أن تعزز بشكل كبير التقييم العملي وتشخيص إدمان المخدرات وتوجيه الوضع السريري بدقة. يمكن للذكاء الاصطناعي أن يلعب دورًا محوريًا من خلال تخصيص العلاج عن طريق تحليل كميات هائلة من البيانات من المريض، والكشف المبكر عن سوء الاستخدام أو الانتكاس، ومراقبة سلوك المريض، وتنبؤ الأفراد المعرضين لخطر كبير لتطوير الإدمان. تُظهر هذه الدراسة المراجعات التي تستخدم الذكاء الاصطناعي وهندسة التعلم العميق في مجالات مختلفة للتنبؤ بهذه الأدوية وسوء استخدامها واستقلابها مع الميزات المعروفة، مما يوفر توجها للدراسات المستقبلية.

الكلمات المفتاحية: الذكاء الاصطناعي، التعلم العميق، إدمان المخدرات .

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1. Introduction

Drug addiction, also known as a substance use disorder, is a complex chronic brain disorder characterized by the persistent seeking and excessive chronic use of drugs despite the negative consequences to mental and physical health and social relationships. It is largely considered a brain illness since the maltreatment of drugs could change the brain over time. Figure 1 and Figure 2, show transforming in the structure of neuro cells and how communications and the dopamine reward pathway change. This collection of neurobiological modifications continues long after the person has quit taking drugs and which might lead to harmful behaviors. Drug use may ultimately develop as a compulsion and can be challenging to undo. Utilizing substance misuse actions, the person's self-control becomes greatly weakened, and they cannot control the demand more and more drugs. Nevertheless, just as with other chronic relapsing illnesses such as diabetes, asthma, or heart disease, drug addiction can be managed effectively (Ceceli et al., 2022; Heilig et al. 2021; Salmanzadeh et al. 2020). Also, it is not strange for someone to relapse and start drug abuse once more. Relapsing, resembling other chronic disorders, requires a revision of therapy. Drug abusers ought to learn how to elude harmful surroundings and associates so that they can create a fresh beginning (Venniro et al.2020; Vafaie & Kober, 2022; Heilig et al.2021).

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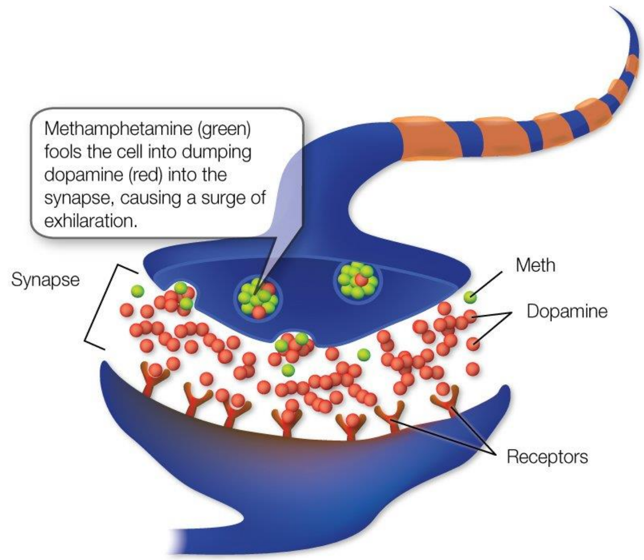

Figure 1: Drug Use Changes the Brain Over Time; Dopamine Levels Increase (Genetic Science Learning Center, 2013).

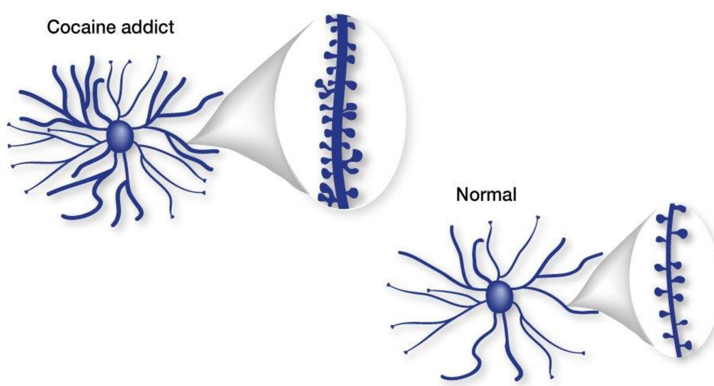

Figure 2: Brain Connections Are Rewired; increase in number, size, and strength (Genetic Science Learning Center, 2013).

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As mentioned above persistent drug abuse results in neurobiological changes, particularly within cerebral regions involved in reward, learning, memory, and cognitive control as illustrated in Figure 3. The potential mechanisms of drug addiction, including the disturbance within synaptic plasticity and kinase signaling cascades, as well as the disruptions in synaptic plasticity and kinase signaling pathways, could all be harnessed by artificial intelligence to achieve the balance of rewarding and aversive cortico−limbic mechanisms without having an exaggeration of psychotic states. (Büttner, 2020) (Quintanilla et al.2023) (Büttner & Büttner, 2021) (Tolomeo et al.2021). In the use of addictive potential assessment, artificial intelligence is useful for discovering important features in pharmacokinetics, pharmacodynamics, and ADME processes, as well as in the identification of risks in specific groups of patients. (Afshar et al.2022) (Ezell et al.2024) (Arif et al.2021) (Gao et al.2023).

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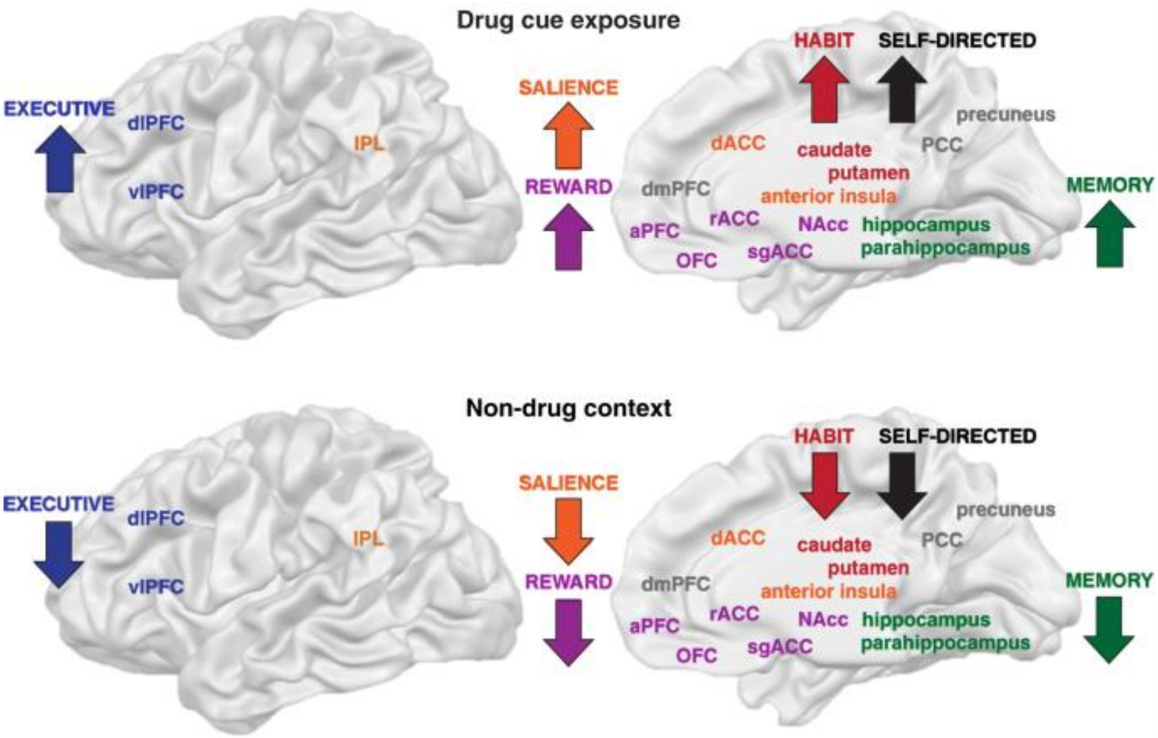

Figure 3: Disturbances in the drug-addicted brain as described by the iRISA framework (Ceceli et al., 2022).

Many researchers have begun to analyze the application of machine learning in the prediction of drug addiction events, such as relapse rates and long-term abstinence, as well as other long-term outcomes, and the results, taken together, have shown that data-driven tools fit patient-level data to predict long-term outcomes such as drug addiction or long-term abstinence with satisfactory performance. (Chekroud et al. 2021) (Khera et al. 2021) (Aggrawal & Pal, 2020). The search for new techniques and tools is essential, especially in the psychiatric field, and for better patient care related to drug addiction. Along with the popular use of artificial intelligence (AI) methods, which involves the recent advancements known as deep learning, as a predictive tool in several scientific tasks, the interest in AI applications to complex biomedical problems, such as those related to addiction, is growing. Many researchers have made significant contributions in drug addiction, in different aspects, such as the variables found to predict addiction relapse. (Nasir and Sassani2021) (Serin et al.2020) (Castiglioni et al.2021). The dropout rate in drug addiction treatment is high; thus, tools that aid in individualized, targeted therapy selection through the prediction of treatment responses, relapse risk, and recovery, among others, could be related and can help reduce the rates of violence, dropout, and failure in these patients. In this regard, it is important to identify and explore the available possibilities to predict drug addiction events through quantitative methods. (Lappan et al., 2020) (Meyerowitz-Katz et al.2020) (O'Connor et al., 2020).

The approaches of advanced artificial intelligence have manifested diverse dynamics and responses of the mammalian brain to potentially addictive compounds with important implications for understanding brain reward circuitry, vulnerability to drug addiction, making animal models more reliable, and brain health in general. Tools such as SIMRI, POD, neural networks, and AI-based responsiveness prediction have risen rapidly in popularity after proving that these could demonstrate an excellent correlation between neural data and drug-likeness models. These may also provide a solution to the problem of drug attrition, also predicting the possibility of unique psychosis-like experiences in the preclinical development stage, thereby preventing human suffering (Deng et al.2022) (Staszak et al.2022) (Beker et al.2020).

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However, few works have systematically summarized recent studies, highlighting the promising uses of AI as a prediction tool for drug addiction (Gupta et al.2021)(Mak et al.2023)(Jiménez-Luna et al.2021). We aim to portray and evaluate recent applications of artificial intelligence in all these aspects and look at how they could significantly influence forthcoming drug testing. The work aims to review the application of different approaches of artificial intelligence and its subfields in addiction research. We concluded by stating some future directions that need to be addressed to transform AI into an effective and efficient tool for the prediction, prevention, and treatment of drug abuse. These technologies can be employed not only in understanding the neurological responses to drugs but also as a prediction tool for clientele at risk of becoming addicted using large databases from CT and MRI imaging to artificial intelligence (Gupta et al.2021) (Mak et al.2023).

2. Neural Mechanisms of Drug Addiction

The dorsal striatum, part of the basal ganglia, plays a crucial role in the development and maintenance of drug addiction. It is heavily involved in habit formation and the transition from voluntary drug use to compulsive drug-seeking behavior through altered neurotransmission and neural plasticity, Figure 4. This circuitry is then proposed to become hyperactive and recruit parts of cortico-limbic-striatal circuits, such as the accumbens, amygdala, medial prefrontal cortex, and insula while exhibiting hypoactivity or disconnected from other parts of the striatal circuitry, which include such structures as the associative and motor striatum. The involvement of cortico-limbic structures is not surprising as it includes areas that impact impulse

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control, negative mood states, and abnormal alpha bias to negative stimuli that are prominent in symptoms of drug and alcohol abuse (Malvaez, 2020) (Zikereya et al., 2023)(Sivils et al., 2021) (Guida et al.2022). This is circuit structure is in part controlled by cortico-striatal receptor mechanisms such as adenosine receptors in the dorsomedial striatum, acetylcholine, and CB1 receptors in the ventral medial striatum (boosting release of GABA from PV interneurons onto NAc-projecting medium spiny neurons) (Chen et al., 2023)(Ferré et al., 2023)(Valjent & Gangarossa, 2021).

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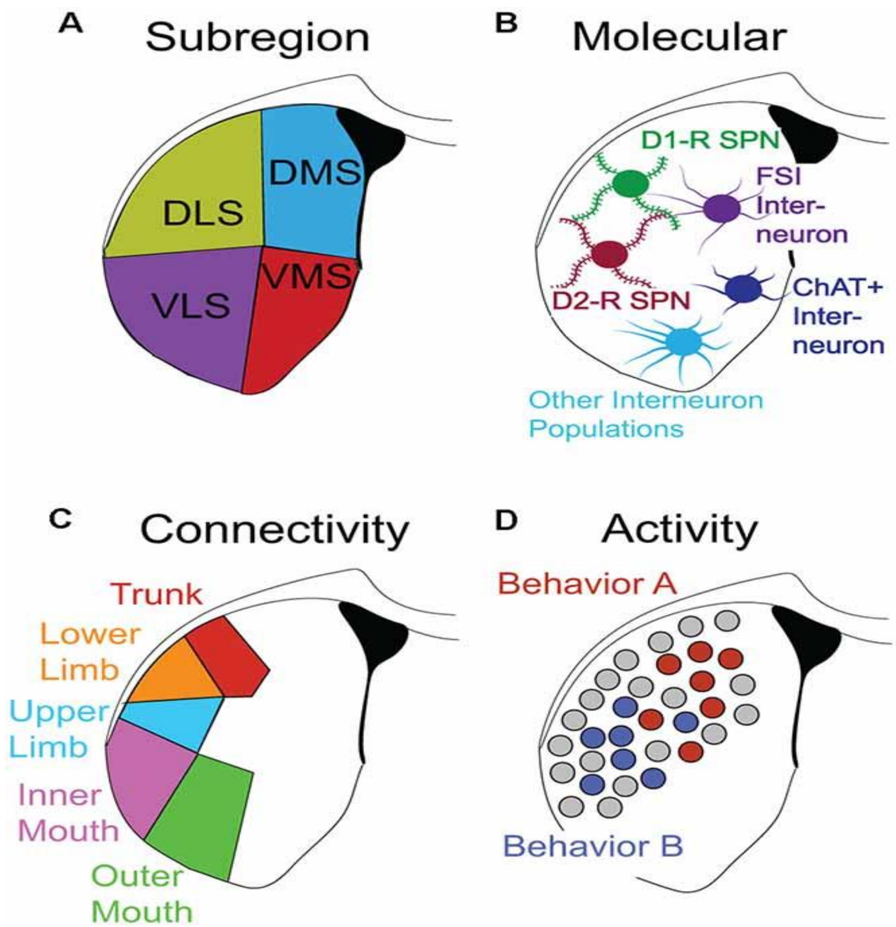

Figure 4: Functional definitions of striatal neurons. (A–D) Different dimensions describing striatal neurons. (A) Striatal subregion. (B) Molecular/genetic: principal striatal cell types include Drd1+ SPNs, Drd2+ SPNs, PV+ FSIs, ChAT+ cholinergic interneurons, and several other important subtypes of interneuron populations. (C) Homuncular: striatal cells preferentially receive inputs from different regions of cortex. Sensorimotor inputs corresponding to specific body parts map to specific regions of the striatum adapted. (D) Task-specific recruitment: segregated clusters of neurons recruited by specific behavioral sequences (Robbe , 2018; Lipton et al., 2019).

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The basis for drug addiction is proposed to involve a dysfunction of the ventrodorsal medial striatum, which is at the terminal release of drug and/or drug-associated stimuli (Basile et al.2021) Figure 5 and Figure 6.

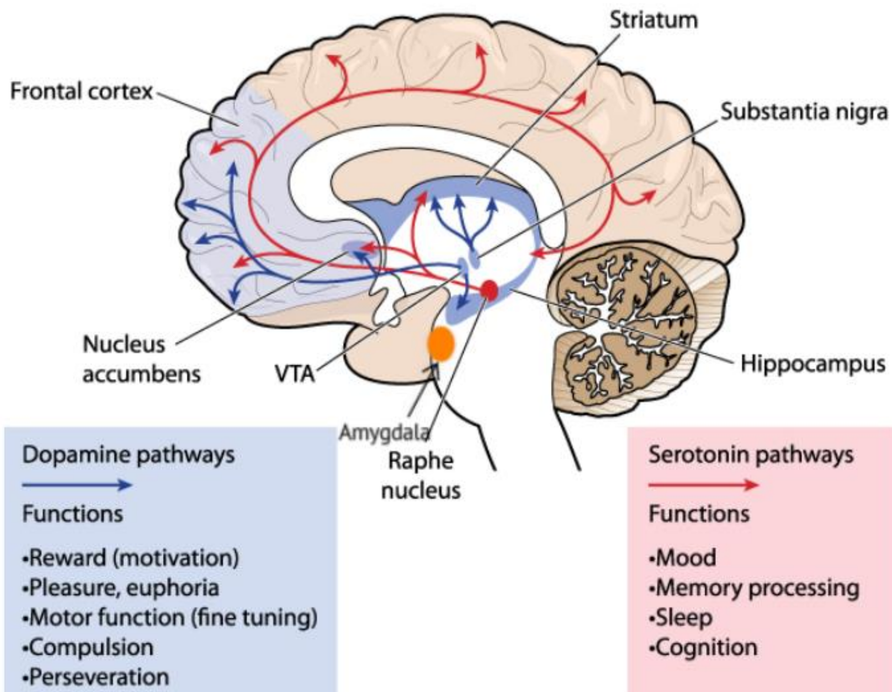

Figure 5: The neural mechanisms that underline transition to long-term

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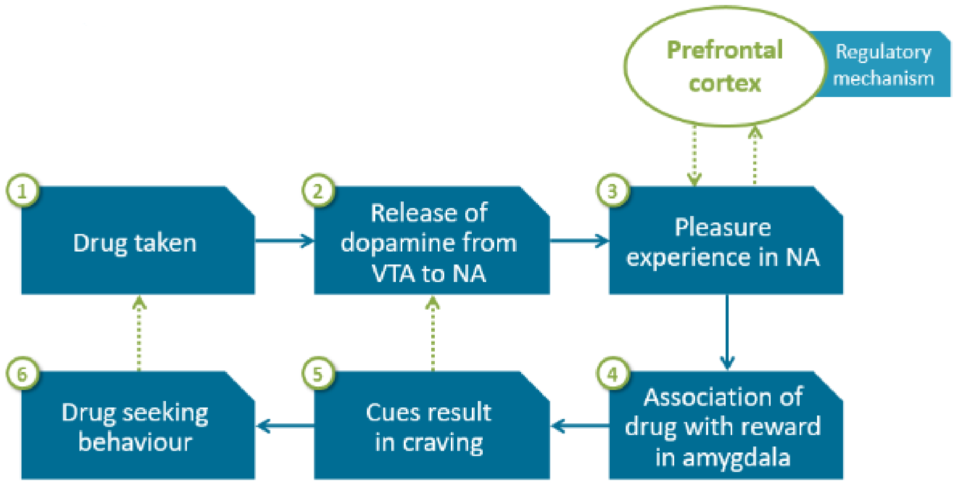

Figure 6: Big Picture of addiction

2.1. Types of Drug Addiction

Drug addiction, or substance use disorder, can involve various types of substances, each with distinct effects on the brain and body, the main categories of drug addiction include stimulant addiction (e.g., cocaine, methamphetamine, amphetamines) (Ciccarone, 2011); opioid addiction like Heroin, prescription painkillers (e.g., oxycodone, hydrocodone, morphine) (Graziani & Nisticò, 2016); depressant addiction (e.g., benzodiazepines, barbiturates) (Griffin et al., 2023); hallucinogen addiction (magic mushrooms LSD) (Griffiths & Grob, 2010); cannabis addiction (Marijuana, hashish) (Huestis, 2002); inhalant addiction (solvents, aerosols, gases, nitrites) (e.g., glue, paint thinners, gasoline, nitrous oxide) (Radparvar, 2023); dissociative addiction like ketamine and dextromethorphan (Farré et al., 2021); synthetic drug addiction like synthetic cannabinoids(Mills et al., 2015). Each type of drug addiction involves different substances with specific effects and associated risks. Understanding these distinctions is crucial for developing effective treatment strategies tailored to the unique challenges posed by each substance.

2.2. Epidemiology and Impact

The addiction problem has been described as a bona fide threat to the healthy development of society. However, the mechanisms that control the formation and inhibition of drug addiction behavior are different for different drugs of abuse, due to person the different properties of drugs. Because we need to be aware of these individual differences in drug addict mechanisms, the discovery of substances that lead to the development of a new drug has started using the phenotypic assessment that analyzes drug addiction behavior. If a person is exposed to significant psychosocial stress as a child or if the mother is exposed to significant psychosocial stress during pregnancy, the risk of developing drug addiction will increase, and ultimately, the gene that controls this mechanism will be identified (Pickard, 2020) (Muela et al., 2022) (Niu et al.2023). In addition, the patient load at addiction treatment centers has been increasing worldwide in recent years. For instance, monitoring system data in the United States revealed a significant increase in methadone use for 10 years ago. The problem is particularly severe in the United States, where opioid addiction is officially designated as an "epidemic." The number of Americans who died of an overdose of a prescription narcotic in 2010 (16,500) is four times that in 1999. In May 2014, the White House reported that the number of American deaths attributable to drug addiction is almost equal to the number of lives lost in car accidents (Cleary2023) (Blair et

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al.2023). Drug overdose death rates, by selected age group, United States, 1999–2016 as Figure 7.

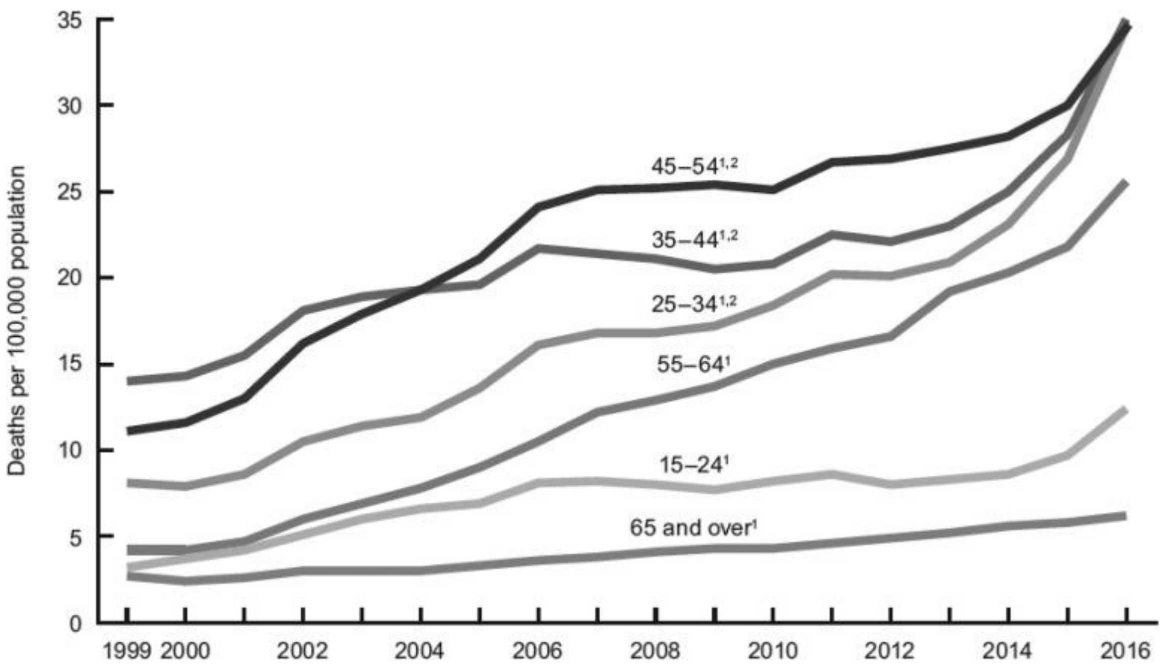

Figure 7: Drug overdose death rates, by selected age group, United States, 1999–2016 (Salmond & Allread, 2019)

According to the World Drug Report (2015) published by the United Nations Office on Drugs and Crime (UNODC), the Middle East and North Africa is a region particularly exposed to illicit opiates and the threat of heroin trafficking. According to UNODC sources, 93% of all confiscations of brown heroin outside Afghanistan (2007–2011 average) occurred in this region, with the majority in Iraq and in the Libyan Arab Jamahiriya. The immense corruption of

Iraqi society during the war is generally considered as a decisive factor in the exacerbation of the Iraqi drug problem (Kurtenbach & Rettberg, 2020)(Das2022).

3. Artificial Intelligence in Healthcare

Artificial Intelligence (AI) is a field within computer science dedicated to developing systems designed to carry out tasks that typically require human intelligence. These tasks include learning, reasoning, problem-solving, perception, language understanding, and making decision. The first AI stage that was examined, is developed using heuristic algorithms to symbolize knowledge as rules in human brains. Statistical-based handling rather than rules was later created based on knowledge acquisition analysis to gain cognitive structure in this term. The completion of novel deep learning models led them to be used explicitly in different regions. Deep learning architectures are modeled based on the basic principles of the human brain. The term 'deep' refers to the model simulates human intelligence to some extent as a deep approach. In terms of the basic property, each hidden layer successively learns comprehensive features of a narrow set of classes, a hierarchy of extraction for data representation. (Anantrasirichai & Bull, 2022) (Markauskaite et al.2022) (Mikalef & Gupta, 2021)

Artificial intelligence underpins several high-impact applications in healthcare, which have been used in diagnosis and personalizing treatment, improving patient care, and optimizing operational efficiency. Recent AI techniques which contribute to knowledge acquisition, representation, inference and validation,

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data exploration, visual imaging, natural language processing, and decision making using various data such as bio-medical images, and clinical and genomics data have facilitated the development of new clinical approaches, solutions, and strategies for patient safety and care. So, it is clear that Artificial intelligence (AI) in general and machine learning (ML) in particular have a lot of success and promise in the potential it holds for various sectors, healthcare being one of the most prominent among all Figure 8 Figure 9.

AI can process vast amounts of data quickly and with high accuracy, aiding in faster and more precise diagnostics and treatments; With global data exceeding 2.9 zettabytes and generating 2.5 exabytes daily, this wealth of information can revolutionize clinical procedures such as drug discovery, development, delivery, prescription, and monitoring (Ghosh et al., 2023; Sakr, 2020; Datta et al., 2021; Bohr & Memarzadeh, 2020).

In this review, we discuss how AI techniques like machine learning, deep learning, and convolutional neural networks have been employed to improve various aspects of healthcare, and we place special emphasis on AI in drug addiction and its computational tools (Alowais et al.2023) (Shaheen, 2021) (Ahmed et al., 2020).

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Figure 8: Application of Artificial Intelligence (AI) in Healthcare (Vijai & Wisetsri, 2021)

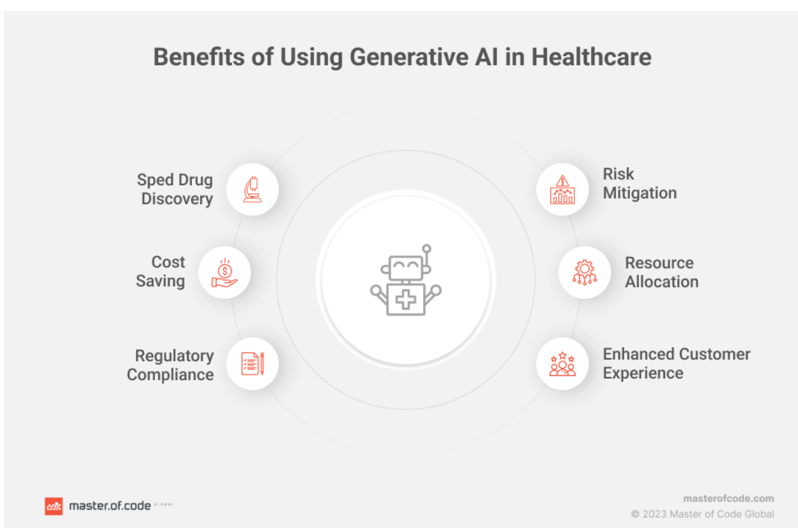

Figure 9: Benefits of Using Generative AI in Healthcare

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4. AI Applications in Drug Addiction

The AI-based techniques offer potential benefits to examine the cause of addiction and to treat the disease derived from the drugs and help the former addicts not to relapse. The domain includes several aspects, such as the cause of addiction, the treatment of the disease due to the drugs, the prediction and diagnosis of addiction, and the warning of addiction, etc. (Rathee et al.2022) (Blanco-Gonzalez et al.2023) (Esmaeilzadeh, 2020) (Kaur et al.2020). The AI-based techniques such as brain imaging study, structural connectivity study, behavior study, medication study, eyeball movement study, and EEG and functional MRI study are used for that. It is predicted that the technology based on AI or machine learning would provide the knowledge to psychiatry experts and help the patients impractically from the various points that make the methodology for analyses more objective than ever and provide a better way to research addiction and treat drug addiction diseases, Figure 10. Therefore, the technological advance in drug addiction issue can be obtained through the AI using. (Aggarwal et al.2023) (Blanco-Gonzalez et al.2023) (Kaur et al.2020).

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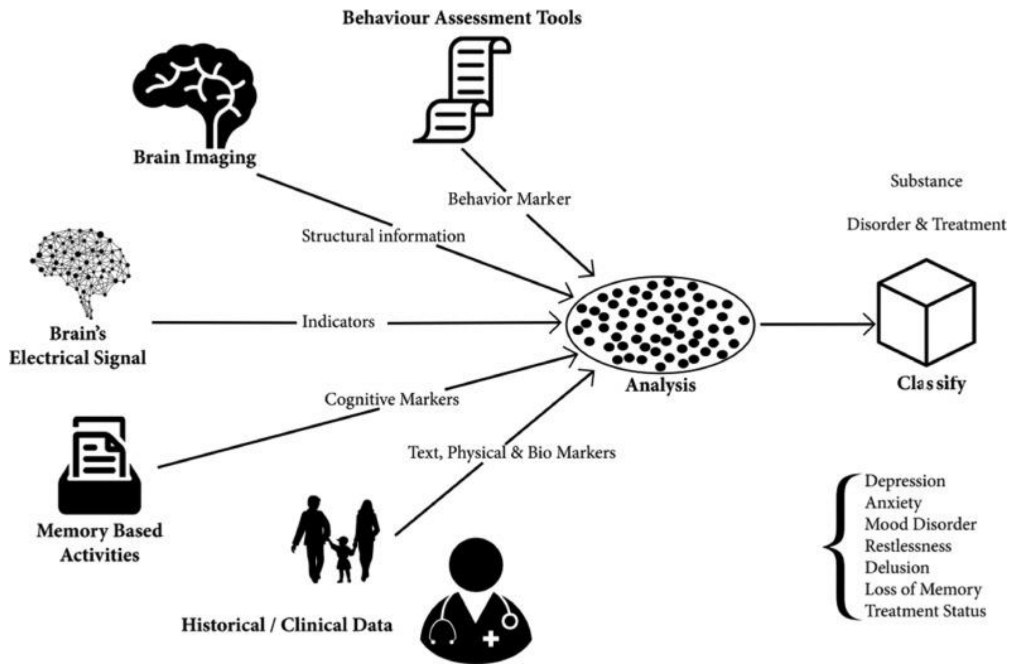

Figure 10: Addiction Analysis Models as per the literature review outcome (Chhetri et al., 2023).

The debate on the potential benefit of AI in drug addiction, especially its predictive powers for drug abusers, has become increasingly attractive. This debate has intensified due to the countless experiments that have been made "in vitro" to obtain reliable information on the characteristics of neuropathways using data from heterogeneous research domains, including genomics, proteomics, transcriptomics and metabolomics. A huge amount of research data extracted from biomedical publications and dispersed "in vivo", thus allowing the acquisition of knowledge for further study, has been made available by the "omics" sciences. This evidence holds great prognostic

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potential since the prediction of drug addiction through AI can be based on different kinds of data (biomarkers) relating to age, sex, genetic history or mutations, brain activity or gene expression, type of substance used in the past, number of consumed substances, kratom/hallucinogen platelet count, and many other variables. (Lin et al., 2020) (Ma et al.2021) (Lancellotti et al.2021) (Zhou et al., 2022)

4.1. Predictive Modeling

The key for an interaction design towards the good habit of a decision maker in question (related to a health issue) is the satisfactory bridge of this particular habit of the decision maker by system feedback. That is, the design of the application should be performed with the help of a robust body of knowledge for psychophysiological and neuronal underpinnings of the planned habit, via, for instance, human psychophysiology experiments and reconsidering addiction models of neuroscience. (Venniro et al.2020) (Khaleghi et al.2022).

A predictive interaction model refers to a predictive algorithm, which is installed in a webpage, that provides positive reinforcement by an entertaining system (resembling a simple point-based game) for the patient's recovery from the health problem in question, for example, alcoholism. Such a game may easily be installed on a computer, laptop, smartphone, tablet, or wristband simply by visiting the relevant webpage online. Patients can play the game at their leisure, before their appointments with their psychiatrist. The application awards them each time they exhibit a behavior, like drinking a specific quantity

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of a product containing alcohol, which is a choice they have denied themselves support for, by giving them points that help them gain a rank in the leaderboard of the game. Winning a rank is a status consolidation for them. (Oh et al.2020) (Arroyo et al., 2022) (Zhang et al.2020).

4.2. Precision Medicine

The current treatment for drug addiction is virtually uniform. Not all patients have the same proclivity for drug addiction. When the same treatment is given, not all patients respond similarly well to the treatment. Ecological fallacy is done when the treatment values are taken as an average. Most drug addicts take drugs in different quantities and frequencies. The predictions are immensely increased when the genetic and other variables of the patient are included. These are usually not reliable predictors at all. For example, even endophenotype is not an established reliable predictor of treatment for addiction. (Poldrack et al., 2020) (Mostafavi et al.2020) (Wand et al.2021). The gene mostly affected by addiction is KKKLC23 or DRD2 gene. However, the drugs that target these genes do not work well, and the drugs that work well do not target them, so the prediction is low (Blum et al., 2023). Behavioral models also play an important role in drug addiction, but most of the environmental exposure is not considered (Trucco, 2020) (Amaro et al., 2021) (Crummy et al.2020).

In precision medicine, treatments are planned based on the genetics and other biological information of individuals. The individuals are provided with the most suitable treatment, which increases the chances of proper treatment. This type of medicine is most beneficial for the patients. (Lopes-Júnior, 2021) (Johnson et al.2021) (Sunil Krishnan et al., 2021).

5. Challenges and Ethical Considerations

At several stages of the non-clinical and clinical research involving drug discovery and development, from the preclinical animal models to human clinical trials, AI can factor during the discovery and evaluation stages to influence the overall cost of evaluation and investment. These concepts allow the reduction or replacement of certain aspects of the evaluation study, without necessarily compromising the translational understanding and clinical goals of the study. The proper integration of these data sets during the design of the study can advance the work of AI in the preclinical and clinical evaluation process. However, with these promising advances, there is a need for an ethical regulatory framework surrounding the utilization of predictive AI in drug addiction studies. The primary aim of AI regulations should be the advocacy for the maintenance of trustworthy AI advances.

Despite the promising advances, whenever AI is applied in novel and multidisciplinary fields, it is also faced with some challenges before its acceptance. The complexity within this context relates to heterogeneous data, inadequate lab experiments, and challenges in the validation of the performance of the AI techniques against actual lab or clinical data. These challenges pose serious limitations when seeking the approval of AI techniques for an actual application in lab or clinical research. (Afshar et al.2022) (Davis et al.2020) (Blanco-Gonzalez et al.2023)

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5.1. Data Privacy and Security

As we come to both praise and fear AI in its current embodiment, we should not forget the major privacy concerns it raises. Historically, privacy concerns related primarily to unauthorized invasions of the confidentiality of our information. While privacy intrusions will still come from these unauthorized accesses, equally grave probabilities arise in the lack of data security. The existence of centralized, combined data accessible by modem has replaced the localized physical records kept by each chasing entity about medical insurance, bank accounts, etc. This ease of remote access has given rise to an unsecured virtual dam of a dangerous technological sort. AI amplifies those adverse consequences through its unique abilities to demolish privacy with much greater efficiency than the older means. (Zhang et al., 2021) (Chen & Esmaeilzadeh, 2024) (Murdoch, 2021) (Majeed et al., 2022)

5.2. Bias and Fairness

Ethical and fair AI is a crucial consideration. Which characteristics should be considered unfair if they show up in the data distribution? For instance, is it appropriate to consider the race or gender of the clinical decision–making patient? What about both, since it is well–documented that we are living in a world characterized by both racism and sexism, with one having a more negative impact when both co–occur? If a clinical AI model is used in the "wild", can we argue that it should avoid learning from these demographic common biases? Finally, even in the absence of any historical wrongdoing, researchers of AI technology must be involved in the societal discourse on its ethical implications to the scientific and general community, as well as to the

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policymakers. (Noseworthy et al.2020) (Meehan et al.2022) (Fletcher et al.2021)

Artificial intelligence models generally assume that the observations utilized during the training phase are accurate and representative of all possible conditions and groups of individuals. However, observational data may reflect the underlying bias of the society from where the data is collected. AI models are trained on these data, and consequently, they may amplify existing biases due to either unequal representation of groups or intrinsic limitations related to the labeling process. This is particularly concerning in the application of AI technology to a domain such as drug addiction. The usage of AI models continues to grow, and there is an increasing risk of using these models for decision-making in high-stakes domains, which could result in unintentional bias during the decision-making process. (Fox et al., 2021) (Yadav & Lewis, 2021) (Hughes et al.2021)

6. Future Directions and Implications

During the adolescence and young adulthood, /the brain undergoes significant changes, leading to impulsive behavior, reduced self-control, and heightened emotional reactivity compared to adulthood. These striking transformations may have important consequences for our understanding of how addiction emerges in young people. In these age groups, it is this contextual information that AI can track over time that begins to make this revolutionary potential for the treatment of addiction supernatural. Around these pivotal years, for once an AI potentially has a great deal to bring to the party. Efforts by clinicians'

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addiction healthcare professionals and policy-setting researchers to enhance addiction surveillance, care, and therapy can be bolstered by AI. In short, AI. has the promise not only to forecast addiction before it shows itself but to halt it in its tracks. (Jones et al.2021) (Icenogle & Cauffman, 2021) (Owens et al.2020)

For teenagers and young adults in the early stages of substance use, predictive AI.s can alert clinicians, caregivers, and friends to the emergence of addiction despite providing few observable clues. This immediate, actionable information means a support proponent or intervention can be brought into play much earlier than is currently possible. AI. has the potential to not only anticipate addiction but also to curb its emergence. By making addiction more relevant and more relatable to individuals experiencing these disruptive changes, AI could help break the cycle of addiction before it starts. (McDaniel & Pease, 2021) (Nowotny, 2021) (Iqbal et al.2023)

7. Research Gaps and Opportunities

It is still an unmet need in the treatment of drug addiction. Mechanistically, lower circuit integration and correlation might be due to pairwise changes in the dendritic spine configurations. The principles that govern these oriented changes and the prediction by them of additional pairwise relationships are an open question. One of the questions to be dealt with in genetic studies of drug use is the predictive power of correlation amongst genetic measures for drug use. Not only the pairwise correlations but also the higher-order mathematical relationships with the SNP sequences used as numerical values might generate a signature for and explanation of the link of sequence-dependent expression to drug use. Indeed, it is well known both for disease association and heritability estimation that a linear dependency may not be the best theoretical model. Further mathematical, genetic, and clinical analyses are needed to evaluate dependency amongst informative SNPs as a tool for predicting addictive behavior or providing evidence for hereditary factors. (Mercer et al.2021) (Zafar et al.2023) (Demchenko et al.2022)

One of the research gaps in drug addiction and artificial intelligence issues is the fact that most of the developed computational models have been based on animal studies. Hence, in the future, comprehensive studies using human studies are necessary to develop intelligent models iteratively. Features required for developing advanced models should include but are not limited to, individual-specific neural circuit information in the human brain. In addition, individual-specific biological and environmental information should also be considered by the developed models. Thus, the biological basis of AI should be improved by collaborative and integrative studies such as connectome-based modeling approaches. Although computational models of addiction are being used extensively, few are trained based on the brain's structural features through AI. According to the study types, they should be classified as predictive based, where hybrid models integrate both deterministic and statistical treatment of the measured data. (Mollick & Kober, 2020) (Gueguen et al.2021) (Heinz et al.2020) (Poisson et al., 2021)

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8. Conclusion

This review found that AI can be a powerful tool in predicting and controlling drug addiction. It can explore the complexities that genetic studies alone cannot fully discover. It can interact with and understand human emotions and behavior. This, in turn, can model synaptic changes in the CNS caused by psychoactive drugs of abuse and ultimately assist human beings in controlling such diseases. The combination of AI, traditional, and complementary medicine could provide the best solution for treating the drug addiction problem.

Despite the promise of AI in helping to treat drug addiction, the whole process, from modeling natural drug addiction in an artificial system to conducting treatment in the human's cognitive system, leaves room for further improvement. Future studies are warranted to understand the mechanisms by which computer models can regulate and improve treatments of such complex disorders. The results from our review warrant future experiments to explore the mechanisms of AI applications concerning drug addiction.

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