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The Hidden Epidemic: Doping in Gyms and the Role of AI in Preventive Health

Damaris Were Ogama

School of Communication and Development Studies, Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya
Email: damarisogama@gmail.com

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Abstract

Doping is an issue associated with elite sports as athletes attempt to enhance their performance to gain an edge over other athletes. However, the prevalence of doping is continuously increasing among recreational users who try to achieve their physical goals in a gym setting. Doping within a gym setting is an issue of public health concern as most individuals use different substances without a doctor's prescription or having proper knowledge of the associated risks of the substances. Also, some users buy nutritional supplements that contain steroids without their knowledge. The paper looks into the use of AI and machine learning as a solution to understanding the trends of gym users who are at risk of doping. The use of AI allows for early detection and behavioral pattern analysis, shifting focus from punitive enforcement practices to preventive care, a crucial element in promoting health training habits within the gym setting.

Keywords

Doping, Gym, Artificial Intelligence

1. Introduction

Numerous studies indicate that physical activity has a positive impact on an individual's health and mental well-being [1]-[3]. Some of the benefits individuals gain from physical activities include a reduction in the risk of heart disease, dementia, cancer and many other conditions [4] [5]. In today's society, achieving such a healthy lifestyle is a priority for many individuals, and one of the ways in which individuals achieve such a lifestyle is by attending gyms [6]. Gyms are critical in promoting activity and healthy living as they offer individuals a structured environment in which they can access equipment and trained professionals [7].

While gyms are traditionally seen as spaces dedicated to health, fitness and well-being, recent studies show a growing change with the normalization of performance-enhancing drugs [PEDs] or doping. Tavares *et al.* (2022) indicate that 1 in 8 fitness participants consider using illicit substances with the aim of getting an aesthetic ideal body or boosting their physical performance [8]. The illicit substances or PEDs individuals use while at the gym to get their desired outcomes tend to cause changes in their behavior, arousal as well as the perception of pain [8]. Research in the area indicates that the illicit substances that gymgoers use include anabolic-androgenic steroids (AAS), human growth hormones, diuretics and erythropoietin [9]. The prevalence of such substances in competitive sports is 73%, while in the fitness context, it is about 70% [8]. A substance such as AAS has numerous applications in the treatment of muscle-wasting diseases and hormonal imbalances [8]. Therefore, the high prevalence of abuse within the fitness community is a growing issue of health concern.

Tavares *et al.* (2022) note that apart from the gym users' high prevalence rates in doping, most of the individuals are considering using PEDs [8]. The motivations of athletes towards doping are determined by their need to improve their performance [10]. According to the theory of planned behavior, behavioral intention towards a specific health behavior is always regulated by a person's attitudes towards the behavior, subjective norm and perceived behavioral control [11]. Studies on the attitudes of the users doping within a gym environment indicate they have positive attitudes towards PED use and have a high risk of recurrent use [8] [12]. With the favorable beliefs towards doping in gyms, it is expected that the increase in the use of PEDs will continue despite their negative impacts on individuals' health.

The main focus of this paper is to explore the prevalence of doping among people who use the gym and ways in which artificial intelligence (AI) can be applied in the gym environment to detect patterns that are associated with the use of performance-enhancing drugs, with the broader aim of informing individuals of preventive health strategies and promote healthy training habits. Exploring such options is critical in reducing the short-term and long-term impact of the recreational use of doping among gym users. Despite the fact that some of the banned substances have approved medicinal uses under professional supervision, individuals need to understand the side effects, which can lead to numerous health issues such as hypertension and even death for some users. Also, it is critical to focus on finding a solution to the problem since not only are some of the side effects of the use of doping overlooked, but the deaths of recreational gym users tend to attract fewer headlines than the deaths of well-known professional athletes.

2. Background and Literature Review

2.1. Doping within Recreational Settings

Doping is not an issue that affects elite sports; it is increasingly becoming an issue in recreational gym use [13]. Elite athletes who use substances banned by WADA tend to face severe sanctions if found guilty [14]. The case is not the same for individuals who dope in recreational settings as they succumb to health issues [11]. In 2014, the European Commission's study on the prevention of doping highlighted a need to obtain information about the prevalence of doping and the types of doping that individuals engage in [15]. The European Commission provided an overview of the practice and legislation regarding the fight against doping in recreational sports [15]. Studies on the prevalence of doping indicate that 18.4% of individuals dope recreationally compared to athletes, with a prevalence of 13.4% [16]. Although the true prevalence of the use of doping for recreational purposes is still not known, fitness centers suggest there is a high risk of individuals doping [16].

The demographic differences towards doping in the recreational arena are difficult to understand. This is due to the fact that it is not easy to compare factors such as sport, age, gender, and the type of substance an individual uses. Hence, different studies report different values for the use of substances that WADA has banned among recreational gym users [16]. Bojsen-Møller and Christiansen (2010) conducted a study with 1398 individuals with respect to their age and gender, affiliation to sports, and the substance they were using [17]. Their study found that 15% of the participants were using AAS or other substances banned by WADA and an additional 15% were considering using such substances [17]. Alkebbeh *et al.* (2022) performed a cross-sectional study with 133 participants to investigate the misuse of over-the-counter (OTC) medication in Syrian gyms [18]. Findings from the study indicate that 35% of the participants were using OTC as well as prescribed medication [18]. Of the individuals taking the drugs, 11% were using protein and amino acids, while about 4% claimed they were using up to 50 different anabolic steroid products as well as other hormones [18]. The most frequently used substance was testosterone [18]. Additionally, doping affects the younger generations. Bird *et al.* (2016) research notes that the illicit use of doping agents is more widespread in society [13].

Ebrahimian Besharat (2020) indicates that the risk of doping within the gym increases due to the fact that people buy products from unauthorized sellers on the back market [16]. In the black market, there is no supervision over the manner in which products are produced or distributed. Lack of proper supervision of the manner in which the products are made results in individuals contaminating their products with steroids to increase their effectiveness and thus attract more users [19] [20]. Furthermore, several studies indicate that nutritional supplements that individuals use tend to be contaminated with substances that WADA has banned without it being written on the label [21] [22]. Such strategies are done with the aim of attracting more buyers at the expense of their health. These instances indicate the need for supervision within a gym environment to ensure that individuals are not victims of such products without their knowledge.

2.2. Public Health Risks of Doping in Gyms

Despite the high prevalence of doping use, research and media attention often focus on its impact on elite athletes to gain a competitive advantage without detailing its health risks [13]. As a result, there is a widespread perception that doping is safe and its adverse effects can be managed, as seen with the majority of the users in recreational settings [23]. However, the reality is quite different since doping has physical and mental health effects and often leads to the death of the users.

Physical Effects of Doping

The physical effects of doping, especially after the use of AAS, include cardiac, neuroendocrine, hepatic and musculoskeletal disorders. The cardiac effects of doping include the development of cardiomyopathy, arrhythmia and hypertension [24]. Also, the consumption of AAS tends to generate dyslipidemia with increased levels of Low-Density Lipoprotein (LDL) as well as a decrease in High-Density Lipoprotein (HDL), which increases the user's risk of atherosclerosis [25]. These different cardiac effects that arise as a result of doping tend to lead to an increase in cardiac infarctions among young individuals. The strain that gym users place on their hearts can result in severe heart conditions [24] [26]. However, the drugs not only affect the heart but also disrupt the normal hormonal functioning of both males and females. In males, using steroids can lead to infertility as well as gynecomastia [27]. In females, it can lead to virilization, irregularities in their menstrual cycle as well as infertility [28]. Furthermore, using growth hormones such as somatotropin more than 10 times the recommended amount in therapeutic doses leads to hypertension, headache and fluid retention [29]. Other undesired effects can include diabetes as well as renal failure [29].

Mental Health Effects of Doping

Doping affects the user's emotional regulation capabilities. Literature demonstrates that doping, especially the use of AAS, is associated with adverse mental issues, which include aggressive behavior [30]. Alongside being aggressive, the individual tends to experience anxiety, low levels of confidence and negative patterns of perfectionism [31]. According to Berger *et al.* (2024), the incidence of mood disorders such as depression has been reported to be 22% among athletes who dope compared to the general population, which is 10% [4]. Also, the prevalence rate of social anxiety is 15% among athletes who dope compared to 2.7% within the general population [4]. Furthermore, Bird *et al.* (2016) study indicates that after doping, AAS tends to be associated with an increased risk of committing suicide among former athletes [13].

2.3. Misinformation and Risk Perception

To use different substances, 48% of the individuals obtained their knowledge from the Internet, while the remaining 52% were from friends and coaches [18]. The users claim that they get a lot of benefits from doping without experiencing any adverse effects. To understand the view of people engaging in doping in recreational sports, Posiadała *et al.* (2010) conducted an opinion poll on 200 people and an anonymous questionnaire on 50 men between the ages of 19 and 45 [32]. Their research finds that most of the individuals engaging in weightlifting, as well as bodybuilding amateurs, were aware of the possible side effects of doping. However, the users were still advocating for doping. To comprehend their behavior, Coquet *et al.* (2018) state that bodybuilders are not different from professional athletes [33]. They are individuals who learn to control different aspects of their lives, such as nutrition, sleep, and recovery [33]. Their dedication to their goals incites the bodybuilders to take risks in order to achieve their targets with regard to their bodies. Unfortunately, Posiadała *et al.* (2010) report that 89% of the individuals who use forbidden substances do not usually consult doctors [32]. However, the users (72%) typically feel the need to consult a doctor when there is a side effect of doping [32].

3. Artificial Intelligence as a Public Health Intervention

Despite the ongoing efforts to create awareness of doping as well as coming up with anti-doping policies for fitness centers in some countries, doping in gyms continues to be a prevalent issue that has a negative impact on the user's health despite seeming to be a solution to achieve their goals [34]. According to research, despite the fact that numerous individuals are aware of the risks that are associated with doping, they are willing to take risks, thus making the issue a public health issue [35] [36]. Therefore, it is essential to protect the health of the population and ensure they achieve their goals without having to experience numerous negative effects on their health. Research on doping in gyms indicates that there is a lack of data when it comes to doping within gyms; therefore, it is really difficult to understand the magnitude of the problems at the community level or the types of drugs that individuals use in order to control their use [13] [16].

BlueDot, a Canadian epidemiological Artificial intelligence platform, showcases the use of machine learning and natural language processing (NLP) to synthesize large-scale data gathering in real-time applications in surveillance of the health of the population [37]. Having consumed up to tens of thousands of news reports, logs of airline ticketing activities, and climate data in more than 60 languages, BlueDot managed to identify the nature of the COVID-19 outbreak on December 31, 2019, accurately predicting the possibility of the disease spreading globally to various countries days earlier than the World Health Organization (WHO) alert [38]. This prognostic capacity was constructed out of grouping oddities in spatial time-series information and showed that AI could spot the most modest alerts of community health hazards before conventional surveillance tools [38]. This model also justifies our methodology: unsupervised clustering of fitness measures, most easily athletic performance levels or intense training sessions, may find evidence of early signs of PED use, without the use of self-report or physiological samples.

Following the pattern set by the epidemiological success of BlueDot, other evidence indicates and shows that unsupervised AI can be used to identify clinically amenable behavioral patterns in health-related fields without the need for self-reported labels [39]. In one recent study, Ontario participants were followed up with unsupervised cluster analyses of their mental health survey, and four different population profiles (including one with clinical-level depressive symptoms and one with high-life stress) were determined [39]. Notably, these clusters not only arise from raw, unlabeled data but also in a meaningful correlation with different patterns of healthcare utilization that emphasize the ability of AI to organize intricate human behaviors into intuitive risk strata [39]. Similarly, cluster detection performed in an unsupervised fashion, like fast training improvement or excessive gym visits, can be utilized to detect people at high risk of PED use. This fact means that this very machine learning framework offers a strong proof of concept on the application of such an approach, as it is demonstrated by transforming otherwise opaque gym behavior into actionable insights.

The insights open up a new critical avenue of opportunity; AI has demonstrated itself in the field of health, where behavioral opacity is a characteristic feature, whereas its use in preventing doping in gyms is unexplored [39]. However, conventional monitoring strategies are somewhat insufficient, as they could only be applied to a group including elite athletes, where more physiological variables could be measured, leaving the public health dynamics present in gym users poorly understood. Henning and Andreasson's (2022) study indicates that there are countries that have taken strict measures, such as criminalizing doping for all individuals, but such efforts do not have a positive impact on the reduction of the number of individuals who engage in doping [23]. Such efforts only focus on punishing the outcome without really focusing on preventing individuals from doping, which is critical as most individuals are willing to take risks to get their desired outcome [23]. To solve the issue, artificial intelligence can be utilized to identify, understand, and mitigate doping among gym users.

3.1. AI-Enhanced Survey-Based Risk Detection

Artificial intelligence is one of the most scalable and practical applications of survey-based risk detection to combat doping in developing countries within the gym. In today's society, gym analytics is critical in allowing facilities to make informed decisions [40] [41]. For the facilities to make informed decisions, they tend to obtain information in terms of attendance, classes, schedules, and peak times in order to ensure that the resources within the gym are being utilized effectively [40]. Such data is critical in allowing gyms to track user attendance patterns, identify drop-off points, and tailor programs that improve member retention. However, such strategies are crucial in understanding the users of the gym to promote healthy habits.

Local gyms should employ voluntary digital tracking tools that allow members to record key workout and health metrics via custom apps or existing platforms. Users of the gym would have to record key metrics such as the frequency of attendance, type of workouts, weight load progression, duration of the sessions and changes in their weight [42]. This is information that the gyms can track using log member check-ins [42]. The information gathered by the gym's application would be anonymized and automatically transmitted for analytical processing. Once the behavioral data has been aggregated, it will be analyzed using unsupervised machine-learning techniques to identify hidden clusters or patterns of user behavior [43]. Specifically, algorithms like K-means clustering can segment gym users into distinct behavioral groups based on their activity profiles [44]. The approach allows for the identification of abnormal user patterns, such as a rapid increase in performance, which may indicate the likelihood of an increased risk of performance-enhancing drug (PED) use [45]. K-means clustering is chosen because it has been effectively used to cluster persons using multivariate behavioral data in an unlabeled situation [46]. It has been effective in identifying latent subgroups with common risk tendencies within the realm of public health analysis techniques (e.g., dietary and lifestyle clustering analyses) [46]. Model performance would be evaluated using the silhouette coefficient as it measures the intra-clustering cohesion and inter-clustering separation, alongside the stability analysis across repeated runs to confirm the robustness of the grouping structure [47]. The different clusters can exhibit high-intensity training characteristics, rapid gains among gym goers, and irregular patterns that are not consistent with natural progression while an individual is in the gym, thus indicating an increase in the risk of doping. This process allows for an educational reach that is targeted to ensure that individuals within the gym are able to get more information about doping.

3.2. Relevance of the Use of AI in a Gym Setting

The use of data collection and AI within the gym setting fits with the evolving digital landscape within the gym setting as well as with the overall health setting. Currently, many individuals utilize apps that track different health metrics [48]. The same technology can be used in gym settings to track users' progress, helping them better understand their training habits and make informed, healthy decisions. This approach supports personal goal attainment while also enhancing member retention and engagement in the gym. However, the same data can be utilized to achieve public health insights without requiring any changes within the gym or users to acquire wearable devices, which would add additional expenses. Therefore, through the use of an app, data can be collected from the users in a noninvasive manner that would seamlessly integrate into the existing gym setup, unlike the invasive tests done on athletes engaging in different sports, which require the use of urine as well as blood tests [16].

Within the gym setting, the use of AI to detect irregular patterns early is essential to allow for intervention, especially since such users are not competitive athletes, but doping still affects their health. Using such a method provides for abnormal patterns to be detected since some of the individuals within the gym setting get involved in doping without directly knowing due to the purchase of contaminated supplements, as indicated by Ebrahimian Besharat (2020) [16]. Similarly, studies suggest that despite there being numerous reports on WADA-banned substances, there are athletes as well as gym users who dope without having enough information about the substances as they rarely consult [16] [49]. Therefore, it is essential to ensure that such individuals are protected from the negative consequences of such substances in a non-punitive manner that judges their morality or treats them as criminals.

3.3. Feasibility of AI Application in Gym Environments

This sort of AI-based monitoring model can be practically implemented in gym settings and can be easily scaled out, but infrastructural, technological, and social factors have to be considered. The solutions offered are based largely on passive behavioral data such as the frequency of use of the gym, the intensity of workouts and performance progression collected through an integrated gym management system of a custom application [50]. Acquisition of these types of data is already being monitored in a variety of higher-end commercial fitness centers through access control systems, equipment use logs, or member-facing Apps [51]. The incremental infrastructural requirement is, therefore, very low, especially when the AI model is integrated into an already present digital ecosystem that gyms currently use to engage their members or monitor their performances.

Technologically, all internally-facing practical implementations depend primarily on the ability to access secured data through a cloud-based data pipeline that can store and preprocess anonymized behavioral data, a modular machine learning backend that is capable of performing unsupervised clustering, such as through K-means or DBSCAN, and a user-facing dashboard that visualizes summarized risk information to relevant authorized personnel [52]. Development of these elements could be done by using well-known open-source frameworks like TensorFlow, Scikit-learn, and Streamlit and hence lower the entry threshold of small and mid-sized fitness establishments [53]. Moreover, the model could be retrained on a periodic basis with new gym-specific data, which allows for improving the contextual adaptability of the model without making significant technical changes [54]. Significantly, since the model will not be using biometric data or noninvasive physiological measures, it will not be subject to substantive ethical and regulatory barriers and will maintain the privacy of the members.

It is expected that users will be able to participate most extensively in the environments where the use of the intervention is put in the context of harm reduction and health optimization but not surveillance. The debate on health behavior monitoring technologies has already revealed that individuals are more willing to agree to participate in the transactions when they do not experience the collection of the data as sanctions but as empowerment [55]. Also, the lack of identification with the AI model of deriving patterns within clusters of individuals instead of the individual labeling phenomenon further helps to eliminate the opposition of both gymgoers and facility managers.

The cost considerations also support the viability of implementation. Initial software development and training of personnel to analyze the output are major costs that can be salvaged through health promotion agencies' partnerships or grants available in the public health area. When implemented, the system will not have much maintenance and can be expanded to facilities without a huge increase in cost. Also, the sustained health outcomes of early intervention, namely, the fewer cases of PED-related heart conditions or mental illnesses, among others, merit the start-up investment on behalf of both public and private health stakeholders.

3.4. Translating AI Detection into Behavioral Intervention

To make the output of artificial intelligence (AI) models of practical use toward developing meaningful public health interventions in the gym, the output has to be transformed into real-world plans that directly relate to adhering to health-promoting behaviors and the prevention of using performance-enhancing drugs (PEDs) [39]. AI detection should not do more than detect clusters of risks and allow a continuum of adaptive, user-centered, and context-specific interventions [56]. This part presents a framework that proposes to use AI-based observations to provide focused educational and preventive approaches while considering the barriers to implementation.

Utilizing Detection Outputs for Personalized Feedback

The unsupervised learning approach based on the selection of variables, including the frequency of training, a sudden increase in performance level, and the long session, would be used to categorize the gym users as high-risk, which could be included in behavioral clustering, allowing for the development of a strong structure on creating individual behavioral information [57]. Such an AI-powered method enables detection of the presence of hidden patterns of usage, which may be related to using performance-enhancing drugs (PEDs) and overcoming the shortcomings of such methods as self-reporting and biological measurement [58]. This kind of behavioral clustering can offer an early prism, according to which unusual training patterns can be identified to enable a proactive approach to steer interventions [58]. The practical means of digital health research prove that the most efficient interventions that lead to awareness building and motivation to change are based on information about concrete behavior scenarios [59]. Although there is no direct feedback system for the user incorporated in the current implementation, the calculated behavioral profiles can be used as a source of tailored educational interventions, coaching interventions, or facilitating conversation as initiated by a gym professional. Also, the subsequent model versions would provide users with contextually relevant senses using the optional interfaces, thus supporting their staying true to the fitness objectives without entering the trajectories of high-risk behavior. This systematic, evidence-based practice makes it even more preventive and individually specific to implement health promotion campaigns in gym settings.

In the case of gyms, this system offers a non-invasive way of encouraging safe training conditions without taking away user autonomy. Personalized correspondence enforces an atmosphere of health responsibility and enables gyms to work against collective patterns without intruding on privacy [60]. Furthermore, the generated anonymized behavioral patterns, which these models promote, present useful data resources to public health researchers, as they allow them to trace the distribution of PED risk among the populations, assess the effectiveness of the implementations, and develop more effective prevention policies [61]. In the end, this model would transform the paradigm of punitive regulation to evidence-driven personalized prevention by aligning the use of AI with the ethical objectives of the public health agenda and providing positive contributions at the user, institutional, and research levels.

Health Education Strategies

The main prevention strategy for performance-enhancing drug (PED) use is the basis of incorporating health education into the gym ecosystem [23]. Engl *et al.* (2019) argue that health prevention and education are much more effective when it is guided by the behavioral data compiled with the help of unsupervised machine learning [62]. Patterns of use, which can include the frequency of visiting the gym, a sudden increase in training weight, and unusual session times, can become the pattern in the use of gym equipment, which AI models can define and mark a specific group of users who may be associated with an increased risk of PED use. This data-driven model of segmentation enables educators and gym administrators to create educational messages and delivery plans sensitive to the observable behaviors within the gym environment and not necessarily tied to health promotion messages that are based on generalized health campaigns [63]. This kind of alignment ensures that prevention does not just focus on evidence-based work but is also responsive to real-life conditions of target groups.

In addition, the behavioral clusters that are discovered with the help of AI may become strong parameters for measuring the effectiveness of health education strategies. An example of how this can be used is given by looking over time to see whether there are changes in size or composition of clusters of high-risk individuals: such could provide a measure of whether educational interventions are having an impact on behavior. This allows for the creation of a feedback loop in which educational programs are constantly optimized and confirmed with the usage data that is anonymized [63]. Moreover, the clustering data gives any researcher a method that is easily scaled and ethically parked in investigating behavior-risk-perception-health outcome relationships in non-elite sporting fields [64]. In such a way, the introduction of AI-enabled behavioral analysis into gym-based health education not only increases the precision of the interventions but also makes the educational system scientifically credible and useful in the view of improving public health.

Behavior Change Interventions

The ability to segment the user base of the gym based on behavioral patterns in terms of the frequency of training, training progression, and workload transitions that can be analyzed via AI is a crucial interface to other interventions that are aimed at changing behavior. Individually, such data can help in determining people whose exercise patterns could be used to estimate the high risk of PED presence. Instead of depending on self-reported intent or observable results, which tend to be inaccurate or delayed, interventions may be advised by measurable deviations in normative training behavior [65]. This enables tailored support routes, such as emotional interviewing strategies, commissioning of individual fitness objectives, and interpolating progress without access to performance-enhancing drugs, all based on real-world usage. The empirical expression of the relevance of interventions, with the personal behavior profiles, is the far greater involvement and cognitive openness [59].

On the institutional level, aggregate behavior data can be used to apply tiered intervention programs by gyms. Once high-risk behavior clusters have been identified, it is possible to more easily deploy in-house counseling resources, put forth specific sessions of peer-to-peer education or set up trigger points that would lead to referral to outside health experts, including, but not limited to, sports psychologists [66]. Furthermore, anonymized aggregate data can be a basis for collaborating with public health officials, as they tend not to have a minute-granular understanding of the state of doping in recreational settings [67]. This allows a population-based approach to behavior change through policy-making, resource distribution, and the development of broad-based preventive plans. Finally, added to gym ecosystems are unsupervised learning models, which promote user integration in individual behavioral insight and community-wide intervention measures, creating an environment conducive to both personal health and system-wide intervention effectiveness.

3.5. Implementation Challenges

Nevertheless, there are challenges in the use of AI in gym-based programs despite its potential. It might be challenging to maintain the interest of the users over time with the application, especially when fatigue or lack of motivation is the order of the day [68]. This should be solved by adding functions that stay relevant and useful, like personal progress tracking or fitness goal tracking with the app. There is also the possibility that not everyone is going to welcome the idea of being categorized along with the behavior we engage in because of the algorithm and in places where the user feels that they are being stigmatized or would instinctively know that they are being spied on [55]. In order to address this, transparency about the importance of handling and using behavioral data should be encouraged so that the users can be assured that the system is not meant to punish their fitness processes but to enhance them [69]. At the institutional level, to be implemented successfully, the personnel working at the gym should be thoroughly trained not only to interpret the resulting behavioral insights provided by the model but also to respond with discretion, empathy, and in accordance with ethical standards [70]. Even when the system is intended to give indicators early [like clustering patterns, which indicate high-risk use], this is perceived as a supplementary device as opposed to a judgment [71]. Similar to other digital health technologies, regular model testing, sustained monitoring, and the protection of user independence should be considered to avoid overreliance on machine decisions at the peril of patient-specific treatment [72].

3.6. Limitations and Ethical Considerations

Although the vision of the proposed AI-based solution provides a scalable, non-invasive means of recognizing patterns of potential PED use in gyms, a range of limitations along with ethical issues should be considered. To begin with, app-based behavioral monitoring works on the basis of the data provided by the user and such information raises concerns of data privacy and informed consent [73]. Even the anonymized, aggregated set of individual-level data on gym usage frequency, performance values or biometric indicators can have reasonable privacy implications concerning monitoring, especially when the user is not fully aware of the extent of data usage [74]. Therefore, the deployment of such a system must be underpinned by a robust content framework. Gym users should receive clear, accessible information outlining the complete data collection and analysis process and its potential uses. The consent process ensures that gym users can voluntarily participate as well as opt out at any time [74]. Special consideration must also be given to vulnerable populations and young individuals under the age of 18 who are also affected by the doping issue and have access to the gym but lack the legal capacity to provide consent independently. In such instances, parental or guardian consent should be obtained [73].

Secondly, the risk of having algorithmic bias is severe. Unsupervised models trained on skewed or non-representative data, such as data from specific socioeconomic groups or urban centers, may come up with misleading models that overreport some behaviors and underreport others [75]. Since such systems lack curation of their datasets and lack transparency in feature selection, they can potentially replicate stereotypes or facilitate false positives, which erodes the reputation of interventions in the field of public health [76].

In addition, the system can be biased concerning the idea of participation. The users who elect to participate in tracking applications are unlikely to be comparable to those with a higher risk of PED misuse, so that the prevalence might be underreported or the pattern of at-risk users skewed [77]. Considerable attention to valid consent frameworks, open data governance, and relentless auditing of algorithmic outputs should consequently be addressed to ensure ethical deployment to prevent abuse or discrimination without abridging the maxim of benefit to the health of the population by early intervention [78].

4. Conclusion

Doping within a gym setting is an issue of public health concern in society due to the high prevalence rate of individuals engaging in doping, including young individuals. Unlike elite athletes, the number of individuals who dope within gyms is not known and numerous individuals suffer the health consequences of doping.

Unfortunately, some individuals dope without their knowledge as they utilize nutritional supplements with misleading labels. Traditional methods of monitoring doping in elite sports, such as urine samples and blood tests, cannot be used in a gym setup. Also, such a method only focuses on the outcome and punishes the behavior without resulting in prevention measures within the society. Collecting data from gym users using an app and employing unsupervised machine learning techniques is a non-invasive pattern detection method for getting to know individuals who may be doping in a gym setting. Such a method can seamlessly be integrated into a gym's normal routine and even allow the gym to assist its users in engaging in healthy training habits. Therefore, this model provides for health education, encourages self-awareness among gym users, and empowers them to ensure that they make informed decisions. Ultimately, such a solution allows for public health systems to intervene in non-clinical spaces where there is no surveillance. Future efforts ought to focus on collaboratively utilizing technology, public health policy and gym management practices to ensure that there is a safer and more transparent fitness ecosystem.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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