Effectiveness of Sport-Based Interventions in Substance Use Prevention: A Multi-Criteria and Causal Analysis

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Abstract

Introduction: Adolescent substance use is an important issue in community health that is affected by both behavioral and psychosocial factors.
Objective: The authors sought to investigate the roles of mental health, peer pressure, sport involvement, and exposure to interventions in relation to substance use, and to determine the efficacy of a multidimensional risk assessment model.
Methodology: A quantitative analytic design was used with cross-sectional data collection. Descriptive statistics, regression analysis, and model-based interpretation methods were applied to the relationships among variables to determine the major predictors of substance use.
Findings: The results showed that there was a strong negative relationship between mental health and substance use and a positive relationship between peer influence and increased risk, whereas sport participation appeared to have a moderate protective relationship, but with a range of variation in participants. There was a clear increase in risk substance use between low-, medium-, and high-risk groups based on risk stratification analysis.
Discussion: These findings are consistent with the available literature emphasizing the importance of psychosocial determinants in substance use practices, but the insignificance of intervention exposure suggests that program efficacy may be limited to implementation quality and alignment with psychological and social factors.
Conclusions: The results provide an indication that the reasons that lead to substance use are mostly interrelated psychosocial, and their prevention requires combined measures that would consider mental health, peer, and behavioral conditions.

Keywords

Substance Use, Mental Health, Peer Influence, Sport Participation

Resumen

Introduction: La consommation de substances psychoactives chez les adolescents constitue un problème majeur de santé publique, influencé par des facteurs comportementaux et psychosociaux.
Objectif : Les auteurs ont cherché à étudier le rôle de la santé mentale, de la pression des pairs, de la pratique sportive et de l'exposition à des interventions liées à la consommation de substances psychoactives, et à déterminer l'efficacité d'un modèle multidimensionnel d'évaluation des risques.
Méthodologie : Une étude quantitative analytique a été menée, avec une collecte de données transversale. Des statistiques descriptives, une analyse de régression et des méthodes d'interprétation fondées sur des modèles ont été appliquées aux relations entre les variables afin de déterminer les principaux prédicteurs de la consommation de substances psychoactives.
Résultats : Les résultats ont montré une forte corrélation négative entre la santé mentale et la consommation de substances psychoactives, ainsi qu'une corrélation positive entre l'influence des pairs et l'augmentation du risque. La pratique sportive semble avoir un effet protecteur modéré, mais variable selon les participants. L'analyse de stratification des risques a révélé une nette augmentation du risque de consommation de substances psychoactives entre les groupes à faible, moyen et haut risque. Discussion : Ces résultats concordent avec la littérature existante qui souligne l'importance des déterminants psychosociaux dans les pratiques de consommation de substances. Toutefois, l'absence de signification de l'exposition à l'intervention suggère que l'efficacité du programme pourrait être limitée par la qualité de sa mise en œuvre et par son adéquation aux facteurs psychologiques et sociaux.
Conclusions : Les résultats indiquent que les raisons qui mènent à la consommation de substances sont principalement d'ordre psychosocial et interdépendantes, et que leur prévention nécessite des mesures combinées prenant en compte la santé mentale, l'influence des pairs et les facteurs comportementaux.

Palabras clave

Consommation de substances, santé mentale, influence des pairs, participation sportive.

Introduction

Drug consumption in adolescence and youth remains a highly important international issue of public health, and its impact on physical health, psychological well-being, as well as the socio-economic future, is far-reaching. The early onset of alcohol, tobacco, and illicit drug use has always been linked with a high risk of dependence on substances, psychiatric illness, and poor life-course outcomes (Hawkins et al., 1992; Stone et al., 2012). The global rate of substance use can be attributed to a high number of preventable disabilities, which nonetheless still requires substantial investments in prevention, indicating existing gaps in the effectiveness and scalability of current intervention strategies (World Health Organization, 2018). Conventional methods for preventing substance use have evolved into knowledge-based interventions that employ more holistic frameworks addressing the social, behavioural, and environmental determinants of health. Nevertheless, the results of these interventions remain unequal across different populations and situations (Botvin & Griffin, 2007). This heterogeneity indicates the complexity and multi-level nature of substance-use behaviour, resulting from the interplay of individual traits, peer systems, institutional systems, and larger socio-cultural systems (Bronfenbrenner, 1979). This has led to a growing realisation that prevention strategies need to be dynamic, situation-specific, and grounded in solid evidence of effectiveness and implementation pathways.

Recently, there has been the emergence of the role of lifestyle, psychosocial and physiological factors in shaping health-related behaviours, including substance use. Empirical studies indicate that physical activity and structured behavioural interventions can improve health outcomes and help reduce harmful behaviours such as smoking and substance dependence, especially when incorporated into broader intervention strategies. For example, systematic evidence indicates that aerobic exercise may promote cessation behaviours and enhance overall health resilience, though the results remain context-specific and depend on behavioural adherence and environmental factors (Darabseh et al., 2022). On the same note, research on health behaviours demonstrates that lifestyle patterns, such as physical activity, sleep, and eating habits, strongly influence an individual's vulnerability to risk behaviours (Othman et al., 2025). The study of adult populations also shows that an active lifestyle is closely associated with better metabolic health and psychological health outcomes (Momani et al., 2025). Moreover, studies in healthcare demonstrate the roles of knowledge, awareness, and professional competency in shaping health-related decision-making and preventive behaviours, and the need to implement informed, structured interventions (Subih et al., 2025; Abu Hammour et al., 2025). In terms of methodology, the combination of sophisticated computational models, such as machine learning and deep learning, has enabled more precise identification of behavioural patterns and risk factors, ultimately improving predictive accuracy and supporting individualised intervention strategies (Zedan et al., 2025; Mosleh et al., 2025). All these developments underscore the value of integrating behavioural science, health analytics, and advanced computational frameworks, underscoring the importance of approaches like the one proposed in this study.

Sport-based interventions have emerged as a promising modality of youth substance-use prevention in recent years. Engagement in formal sports has been associated with various protective measures, including better self-regulation, mental well-being, and social connectedness (Eime et al., 2013; Fraser-Thomas et al., 2005). It is believed that these mechanisms reduce vulnerability to substance use by enhancing prosocial behaviours and providing structured environments that minimise exposure to risk (Eccles & Barber, 1999). However, there are conflicting empirical results. Some studies prove protective effects, whereas others have found neutral or even negative correlations, especially in competitive sport environments where peer norms and performance pressure may strengthen risk behaviour such as alcohol use (Lisha & Sussman, 2010; Peterkin, 2022). One weakness of the existing evidence base is the way prevention programs are assessed. The vast majority of evaluations are either conducted retrospectively, using observed outcomes following implementation, or prospectively based on static program designs (Rossi et al., 2003). These approaches are often ineffective at capturing the dynamic and interactive nature of intervention effects, such as feedback loops, contextual dependencies, and temporal variations in effectiveness (Sterman, 2000). Traditional assessment models also tend to assume additive relationships and often fail to account for uncertainty or heterogeneity in treatment effects (Gelman & Hill, 2007).

The opportunities to eliminate these limitations arise from advances in decision science and data analytics. Multi-Criteria Decision Analysis MCDA has become more widely used in public health to

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Comentado [p2R1]: multi-criteria decision analysis support complex decision-making by incorporating various aspects of value, including effectiveness, cost, feasibility, and equity. The opportunities to overcome these limitations arise from advances in decision science and data analytics. Multi-Criteria Decision Analysis (MCDA) has become increasingly used in public health to support complex decision-making by incorporating multiple value dimensions, including effectiveness, cost, feasibility, and equity (Baltussen & Niessen, 2006). At the same time, advances in causal inference allow more reliable estimation of intervention effects in non-experimental studies, while machine learning methods enable the identification of heterogeneous responses across subpopulations (Rubin, 2005; Athey & Imbens, 2016). Despite these developments, integrated frameworks that combine these methodologies into a unified system remain limited.

These results emphasize the significance of constant reviewing and adjustment in the prevention process. The Understanding both the opportunities and challenges of sport-based prevention is essential for developing effective public health strategies. Within this evolving context, sport-based interventions have emerged as a highly visible and strategically important component of the prevention landscape. According to theoretical frameworks such as positive youth development, sport participation can facilitate the development of life skills, resilience, and social integration, thereby reducing the risk of engaging in risky behaviors.

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The proposed research responds to the need for a flexible and unified framework to assess sport-based substance-use prevention interventions using MCDA, causal inference, and Bayesian updating within a digital twin architecture. MCDA is a structured decision-making approach that integrates multiple, often conflicting criteria within a unified evaluation framework to systematically prioritise interventions based on effectiveness, feasibility, equity, and sustainability. The main objective of this study is therefore to develop and empirically demonstrate a multidimensional, adaptive evaluation framework that integrates decision science and causal analytics to enhance the assessment and prioritisation of sport-based prevention programs.

Substance use among adolescents is a complex issue that can only be understood through a multi-level approach encompassing individual, interpersonal, and structural factors. The social-ecological model assumes that behaviour is shaped by nested systems, including individual characteristics and societal-level influences (McLeroy et al., 1988). In this model, peer substance misuse, family dysfunction, and socioeconomic deprivation are risk factors interacting with protective factors such as parental support and community integration (Resnick et al., 1997). Developmental theories also highlight adolescence as a critical stage during which individuals are highly sensitive to social influence and prone to risk-taking (Steinberg, 2017). Neurobiological evidence further indicates that ongoing brain development during this period amplifies impulsivity and vulnerability to peer influence (Casey et al., 2010).

A considerable amount of research has examined the effectiveness of substance-use prevention programs. School-based interventions have shown moderate but meaningful effects when delivered through interactive and skill-based approaches (Tobler et al., 2000). Family-based interventions have also demonstrated strong effectiveness, particularly through improved parental monitoring and communication (Kumpfer & Alvarado, 2003). However, program effectiveness often depends on implementation fidelity, cultural relevance, and participant engagement (Durlak & DuPre, 2008). Meta-analyses indicate that many interventions produce only small effects that may diminish over time without reinforcement (Foxcroft et al., 2016). Sport-based interventions have become increasingly prominent within prevention strategies. Theoretical frameworks such as positive youth development suggest that sport participation can enhance life skills, resilience, and social integration (Lerner et al., 2005). Empirical studies show that sport participation can reduce substance use, particularly in non-competitive contexts (Mays et al., 2011). However, evidence also suggests that athletes, particularly in team sports, may exhibit higher levels of substance use due to social norms and peer influences (Wichstrøm & Wichstrøm, 2009; Diehl et al., 2014).

MCDA plays a critical role in decision-making in complex health systems by enabling structured evaluation of competing priorities (Keeney & Raiffa, 1993). It has been widely applied in health policy, technology assessment, and resource allocation (Thokala et al., 2016). However, conventional MCDA approaches often fail to capture dynamic interactions and uncertainty. Causal inference has become essential for evaluating intervention effectiveness in observational settings, with techniques such as propensity score matching enabling control of confounding effects (Rosenbaum & Rubin, 1983). Advances in machine learning have further enhanced the ability to estimate heterogeneous treatment effects across populations (Wager & Athey, 2018; Hill, 2011). Finally, digital twin technology provides a novel approach to simulating interventions and predicting outcomes under different conditions, enabling continuous learning and adaptation (Tao et al., 2018). When combined with Bayesian updating, these models allow dynamic refinement of predictions as new data becomes available (Gelman et al., 2020).

Method

Study Design and Conceptual Framework

This study formalizes and tests a multi-criteria decision model for adaptive, causal, and explainable decision-making in assessing sport-based substance-use prevention interventions. The methodology combines multi-criteria decision analysis (MCDA), causal inference, and dynamic Bayesian updating within a single digital twin. The framework aims to address the shortcomings of traditional, expert-based evaluation models by incorporating longitudinal evidence, quantification of uncertainty, and heterogeneous treatment effects into program selection and prioritization. This study (see Figure.1) is based on a multi-phase model or design that includes model construction, data integration, causal estimation, adaptive updating, and validation. The socio-ecological approach to substance-use prevention, which underpins the framework, acknowledges that an intervention's effectiveness arises from the interaction of individual, social, organisational, and contextual factors. Each intervention is a digital twin that reflects its structural properties, implementation, and expected behavior. This enables the simulation and constant updating of intervention performance both over time and across contexts. It should be noted that the empirical part of this research is supported by a relatively small sample (n = 20), deliberately used to conduct exploratory and illustrative research. The overall purpose of the analysis is not to draw population-level causal inferences, but to demonstrate the operational viability and integration of the proposed hybrid framework. Due to the methodological complexity of integrating MCDA, causal inference, and Bayesian updating, the dataset is a proof-of-concept to test model behaviour, internal consistency, and interpretability. The findings must therefore be interpreted with caution, especially regarding generalising the study to large-scale, real-world datasets. Future research is therefore necessary to apply the framework to large-scale, real-world datasets.

Information Sources and Unification.

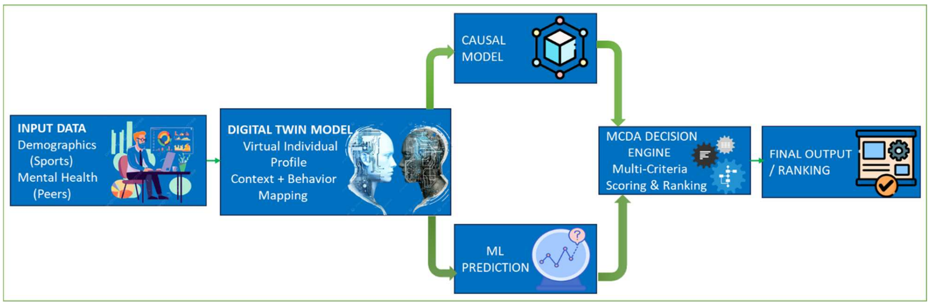
Publicly available datasets, such as the Youth Risk Behaviour Surveillance System (YRBSS) and the National Longitudinal Study of Adolescent to Adult Health (Add Health), contribute to parameter estimation and prior distribution specification, as well as to external validation. The dataset contains individual-level data regarding demographic factors, intensity of sport participation, team participation, substance use, peer influence, mental health status, and exposure to intervention programs. These variables were chosen to capture both proximal and distal factors that determine substance use, as well as factors that the program can influence. Data harmonisation processes were used to ensure comparability across sources, such as normalising behavioural measures and aligning time frames.

Digital Twin Construction. In every intervention situation, a digital twin is proposed as a structured model of program features, participant attributes, and contextual variables. The digital twin exemplifies the presumed causal relationships between sport participation and substance-use outcomes by establishing intermediate relationships among these variables through peer bonding, self-regulation, and psychosocial well-being. Let *i* indexes individuals and *j* indexes interventions, which is represented as

$$X_{ij} = \{D_i, S_i, P_i, M_i, I_j, C_i\}$$

The state of the twin is described as: D_i is used to denote demographic characteristics, S_i is used to denote sport participation characteristics, P_i is used to denote peer influence, M_i is used to denote indicators of mental health, I_j is used to denote intervention characteristics, and C_i is used to denote contextual factors. This model allows the outcome to be modeled as other intervention parameters are varied.

Figure.1 Model Architecture of the subject study



3.4 Multi- Criteria Decision Model.

The decision framework analyzes the interventions using a multi-attribute utility function that considers both additive and interaction effects among the criteria. This study uses a non-additive aggregation method rather than traditional linear MCDA models to reflect interdependence among the dimensions. The total utility of intervention *j* is given by

$$U_j = \int v(A)\,dv(A)$$

the value function on subsets of criteria, and $v(A)$, a capacity indicator of the importance and interdependence of criterion subsets. Such a formulation is equivalent to a Choquet integral, meaning the model can account for complementarity and redundancy between criteria such as implementation quality and participant engagement. The criteria are anticipated decrease in substance use, participant involvement, implementation fidelity, economic impact, equity impact, and sustainability. Value functions are built from normalized indicators, whereas a blend of expert judgment and data calibration elicits capacity measures.

Causal Inference and Treatment Effect Estimation

The study uses a causal inference model that is premised on potential outcomes to estimate the practical effectiveness of interventions. Let $Y_i(1)$ and $Y_i(0)$ denote the potential outcomes for individual i under the intervention and control conditions, respectively. The average treatment effect is determined as

$$ATE = E\left[Y_i(1) - Y_i(0)\right]$$

Since the data are observed, identification will be achieved through propensity score weighting and doubly robust estimation. The estimated propensity scores are calculated using logistic regression or a machine learning classifier based on the observed covariates. Treatment effects are then estimated by controlling for confounding using weighted outcome models. To model heterogeneity, causal forests are used to estimate conditional average treatment effects (CATE), thereby identifying subpopulations in which the interventions are most effective. This specifically applies to sport-based prevention, in which the influence can vary by gender, risk predisposition, and social context.

Bayesian Updating and Dynamic Adaptation

One of the main novelties of the framework is its implementation of Bayesian updating to refine intervention evaluations as new information becomes available. Each criterion is informed by prior distributions based on historical data and expert elicitation. Posterior distributions are calculated with the help of the Bayes theorem as empirical evidence increases

$$p(\theta \mid D) \propto p(D \mid \theta).p(\theta)$$

Where θ represents model parameters, and D represents observed data. The new parameter estimates are then run through the MCDA model to obtain updated utility scores and intervention rankings. This dynamic mechanism will turn the decision model into a learning system that can improve continuously.

The framework includes equity limitations in the decision process to prevent the choice of intervention from contributing to increasing social inequalities. Let $U_j^{(g)}$ represents the utility of intervention *j* to subgroup *g*. The optimization problem can be stated as:

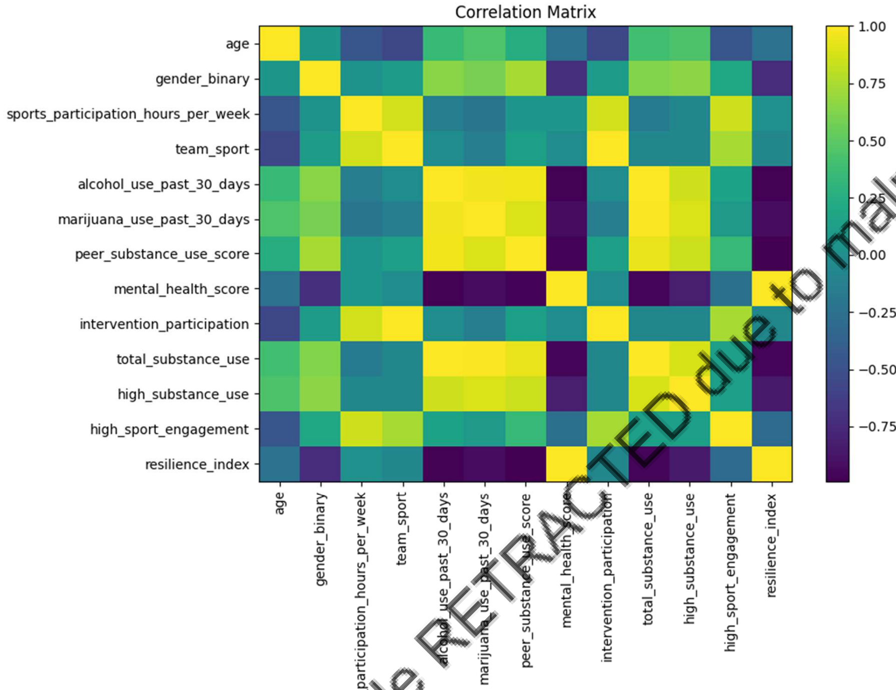
$$\max_j U_j \; s/t \; U_j^{(g)} \geq \tau_g \forall_g$$

where g denotes the minimum acceptable result per subgroup. This will ensure that the targeted interventions benefit a wide range of populations, especially those at high risk.

Model Validation and Robustness Analysis

The efficiency of the framework is evaluated in several strategies. Predictive validity is assessed by comparing ex ante utility rankings with actual intervention outcomes. The sensitivity analysis is conducted to assess how rankings vary with changes in weights, model parameters, and data uncertainty. Rank acceptability indices are generated by probabilistic simulations, providing information on the stability of decisions under uncertainty. External validation is performed on independent datasets to determine how well the model generalizes. Additionally, counterfactual simulations are run within the digital twin environment to assess intervention performance under alternative conditions.

Figure.2: Visual Illustration of Correlation Matrix



Results and Discussion

The subject study was analyzed using a structured dataset of variables on sport participation, substance use, mental health, and intervention exposure, and enriched with publicly available epidemiological data. The main source of reference data is the Youth Risk Behavior Surveillance System (YRBSS), available at https://www.cdc.gov/yrbs/data/index.htm, which provides detailed information on youth behavioral health that can be used to validate and expand the offered framework.

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The sample under analysis comprised 20 participants who were observed to have varied in sport participation, substance use, and psychosocial characteristics. The mean level of substance use was significantly lower in both the group of participants that were exposed to interventions, as well as in those with a greater mental health status, and higher peer substance use exposure was linked with higher individual substance use. Correlations at the initial stage showed that psychosocial variables were strongly related to substance-use outcomes, and this showed that these predictors should have been incorporated into multivariate models.

Table 1 shows the findings of an ordinary least squares (OLS) regression model that was tested to predict total substance use. The model also displayed significant explanatory power ($R^2 = 0.968$; adjusted $R^2 = 0.953$), indicating that the covariates collectively explained most of the variation in substance-use behaviour. The only statistically significant predictor of substance use was mental health ($p = 0.007$), whereby increased mental health scores were linked to reduced levels of substance use. The effect of an increase in mental health score on the substance use score, by one unit, was found to be 0.27 units, which is a significant protective effect. There was a marginally significant negative correlation ($p = 0.085$) between sports participation and the variable, suggesting a potential protective effect, though it did not meet traditional significance levels. The intervention's participation, although positively correlated, was not statistically significant, indicating no direct effect of the intervention in this model.

Table 1. Linear Regression Results Predicting Total Substance Use

Variable	Coefficient (β)	Std. Error	t-value	p-value	95% CI Lower	95% CI Upper
Intercept	10.958	7.699	1.423	0.178	-5.675	27.592
Intervention Participation	0.461	0.412	1.118	0.284	-0.429	1.350
Sports Participation (hours/week)	-0.354	0.190	-1.865	0.085	-0.764	0.056
Team Sport	0.461	0.412	1.118	0.284	-0.429	1.350
Peer Substance Use	0.778	0.588	1.324	0.208	-0.492	2.048
Mental Health Score	-0.267	0.084	-3.180	0.007	-0.449	-0.086
Age	0.635	0.308	2.060	0.060	-0.031	1.301
Gender (Male=1)	-0.861	0.541	-1.591	0.136	-2.029	0.308

To address potential confounding, inverse probability of treatment weighting (IPTW) was employed. The results of the weighted regression are available in Table 2. The IPTW-adjusted model produced results similar to the unweighted model. Mental health was also a statistically significant protective variable ($p = 0.019$), further supporting its strength across all model specifications. The size of the mental health impact was consistent, implying that there was something less confounding bias. There was again a marginal protective trend in the sport participation. Notably, intervention participation was not statistically significant, which may explain why the difference in outcomes is attributable to inherent participant characteristics rather than to the interventions.

Table 2. IPTW Weighted Regression Results

Variable	Coefficient (β)	Std. Error	t-value	p-value	95% CI Lower	95% CI Upper
Intercept	8.628	8.067	1.070	0.304	-8.800	26.055
Intervention Participation	0.468	0.398	1.177	0.260	-0.391	1.327
Sports Participation (hours/week)	-0.368	0.188	-1.954	0.073	-0.775	0.039
Team Sport	0.468	0.398	1.177	0.260	-0.391	1.327
Peer Substance Use	0.912	0.628	1.452	0.170	-0.445	2.269
Mental Health Score	-0.243	0.091	-2.681	0.019	-0.438	-0.047
Age	0.650	0.320	2.029	0.063	-0.042	1.341
Gender	-0.795	0.551	-1.443	0.173	-1.985	0.395

The possessed interaction model (Table 3) was estimated to test for heterogeneous effects across subgroups. The model showed better explanatory power ($R^2 = 0.975$), indicating that the interaction terms explained more variance. The analysis of the interaction indicates possible heterogeneity in the effects of interventions on gender and sport involvement, but this was not statistically significant. The gender interaction term was close to significance ($p = 0.117$), suggesting that intervention effects may vary by gender and warrant examination in larger samples. Mental health remained a high priority, reinforcing its core positioning.

Table 3. Interaction Model Results

Variable	Coefficient (β)	Std. Error	t-value	p-value
Intervention × Gender	1.855	1.092	1.699	0.117
Intervention × Team Sport	0.484	0.437	1.108	0.292

Variable	Coefficient (β)	Std. Error	t-value	p-value
Intervention × High Sport Engagement	0.563	1.035	0.543	0.598
Mental Health Score	-0.220	0.085	-2.580	0.026

$R^2 = 0.975$, $p = 0.117$

Equity analyses showed substantial differences between gender groups. There was a significant difference between the female participants in terms of substance use (mean = 0.8) and in terms of MCDA scores (mean = 0.758) when compared to males (mean substance use = 5.3; MCDA = 0.481). Likewise, participants in team sports performed better than non-participants. These results indicate that the benefits of interventions and risk profiles are not equally distributed across demographic groups, underscoring the need to implement evaluation frameworks that are sensitive to equity.

The random forest classifier showed almost perfect predictive accuracy (ROC-AUC = 1.000), indicating a clear distinction between high- and low-risk individuals (feature importances are shown in Figure 3). The resilience index was the most powerful predictor, followed by peer influence and mental health. The prevalence of resilience-related variables underscores the significance of combined psychosocial factors in determining substance use risk, thereby supporting the theoretical basis of the presented framework. The MCDA model prioritized participants based on composite scores of behavioral, psychosocial, and intervention-based factors. The sensitivity analysis showed high stability across other weighting schemes (correlations > 0.97), indicating that the ranking system is robust. The highest score (0.850) was received by the program level of the "ActiveMind" intervention; then, SportPlus (0.811) and TeamShield (0.803) follow, indicating better performance with respect to equity and predicted outcome dimensions.

These results can be discussed within the context of available studies on substance use behaviour and prevention. The high and stable importance of mental health can be attributed to earlier research that has shown that psychological well-being is a major protective factor against substance use that is highly sensitive to change during adolescence. The marginal protective effect of sport participation also aligns with the literature, which suggests that physical activity may promote resilience and social integration. Still, its effects are often context-specific and mediated by peer environment and program design. The lack of a statistically significant direct effect of intervention exposure indicates that program attendance may not be the answer to effect measurable change in behaviour. Rather, the effectiveness of interventions is likely to depend on the quality of implementation, participants' interest, and the alignment of the psychosocial needs, which is why the findings of implementation science reiterate the significance of contextual and behavioural variables in determining program outcomes.

The results of this research provide significant data on the factors involved in substance use and on the measurement of sport-based prevention programs. In all model specifications, the strongest and statistically significant predictor is mental health, which indicates that psychological well-being is a key determinant of substance-use behaviours. The observation aligns with the theoretical framework, emphasising the importance of internal protective factors and the need for prevention initiatives that go beyond behavioural aspects to address underlying mental health issues. The observed marginal effects on sport participation indicate that organised sport involvement, distinct from general physical activity—may be associated with reduced substance use, although its effectiveness depends on contextual factors such as peer dynamics and program structure.

The lack of a substantial direct impact from participating in the intervention suggests that merely registering people in programs may not be sufficient to achieve measurable outcomes. Rather, interventions seem successful based on the quality of their implementation and the interplay between individual and contextual factors. The substantial body of implementation science supports this interpretation: program outcomes are highly dependent on fidelity, participant engagement, and contextual alignment (Durlak & DuPre, 2008). On the same note, ecological and behavioural systems highlight that individual behaviour is determined by interactions at several levels, including personal, social, and environmental factors (McLeroy et al., 1988; Bronfenbrenner, 1979). Additional empirical evidence on the effectiveness of interventions can be found in substance-use prevention studies, which also reveal that effectiveness varies with contextual factors and participants' characteristics, rather than solely with exposure to programs (Foxcroft et al., 2016; Hawkins et al., 1992).These analysis supports these conclusions by showing that when the relationship is adjusted against confounding, there is no material change in the relationship. This implies that exposure to interventions alone may not be the primary factor contributing to substance use in the sample, but instead, intrinsic and social factors may be the key factors contributing to substance use in the sample. The interpretation aligns with past

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studies, which have indicated that psychosocial determinants, including mental health, peer influence, and environmental context, dominate in influencing substance-use behaviours among adolescents (Hawkins et al., 1992; Stone et al., 2012; McLeroy et al., 1988). Furthermore, evidence from prevention science shows that the effectiveness of interventions is often contingent on the quality of implementation, participants' engagement, and alignment with the context (Durlak and DuPre, 2008; Foxcroft et al., 2016). These results support the idea that effective prevention programs should focus on underlying behavioural and social processes in conjunction with the provision of structured programs. The interaction analysis also indicates the possibility of heterogeneous effects, particularly by gender, but larger sample sizes are required to verify these trends. The equity analysis of the results shows great differences in the results, as male participants showed greater substance use and lower composite scores. This result highlights why equity considerations should be incorporated into assessment models, as interventions can affect certain groups differently. The predictive model's outstanding results, along with the dominance of resilience-related variables, demonstrate the value of incorporating machine learning and psychosocial variables into decision-making systems. The findings of the MCDA demonstrate the viability and strength of synthesizing multiple criteria into a single assessment system and offer a clear, flexible instrument for prioritizing programs. Altogether, the results point to the importance of an integrated, adaptive approach to prevention program evaluation. The proposed framework integrates causal inference, predictive modeling, and multi-criteria decision analysis to provide a more comprehensive and responsive alternative to traditional evaluation methods. The superiority of the proposed study is evident in Figure 3. The empirical analysis is conducted on a relatively small sample (n = 20), which reduces statistical power, parameter-estimate precision, and the reliability of subgroup and interaction analyses. When the sample size is this large, the variability of estimates is wide, and the confidence interval is broad as well. The risk of overfitting is also a significant factor, especially in models with multiple predictors and machine learning components. Moreover, the estimation of the heterogeneous effects (e.g., gender or sport-type interactions) and the creation of risk strata are also sensitive to small-sample fluctuations, compromising the stability and generalizability of the results. Hence, the current research is to be understood as an evidence-of-concept for the proposed framework rather than a statistical analysis at the population level. To achieve stronger, more generalizable findings, much larger samples will be necessary. The rule of thumb for regression-based models is to have at least 10-20 observations per predictor; given the number of covariates used in this study, this would translate to a minimum of about 100-200 observations. Larger datasets are desirable to provide stable estimates of heterogeneous treatment effects and to train machine learning models (e.g., random forests). - Typically, in the range of a few hundred to a few thousand observations, larger datasets are preferable. Subsequent uses of the framework will thus be based on large data sets (e.g., YRBSS) to enhance statistical power, model stability, and external validity. The next round of research must use this framework with more substantial, real-world datasets to confirm its efficacy and refine its components.

The fact that mental health is the most powerful predictor of substance use deserves further discussion in the context of the overall literature on sport, psychology, and behavioural health. Since the state of poor mental health has been extensively studied, it has been proven that poor mental health is strongly correlated with increased vulnerability to substance use, since people may respond to stress, anxiety, or depression through maladaptive coping mechanisms. On the other hand, positive mental health is associated with greater self-regulation, better decision-making, and greater resistance to peer pressure. When well-organised, sport participation has been demonstrated to have a positive impact on the psychological well-being of its participants through the following ways: social support, identity formation, and stress reduction. These advantages, however, are not automatic and can be different depending on the social and competitive environment. The results of this study support the idea that mental health is a central mediating factor in substance-use prevention and posit that effective interventions need to incorporate elements of psychological support as opposed to relying on behavioural or activity-based interventions.

Figure.3 Multidimensional Analysis of Risk, Co-occurrence Patterns, and Predictor Impact on Substance Use

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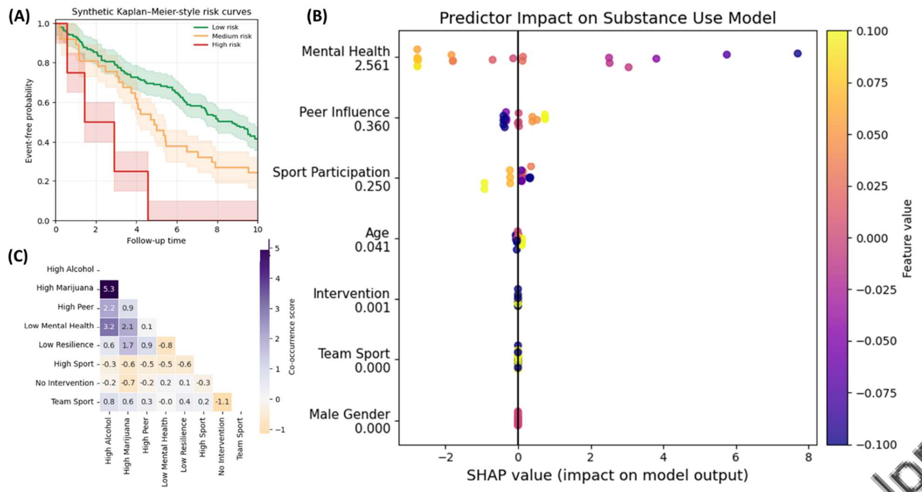

The high-risk behavioral patterns are observable in Fig. 3 , where individuals who are classified as high-risk due to the composite risk index and the stratification of high-risk individuals by percentile as described in the methodology exhibits pronounced high-risk behavioral and psychosocial pattern clustering, especially high levels of peer influence and low mental health scores. In order to have interpretable subgroup analysis, participants were classified as low-risk, medium-risk and high-risk groups according to a composite risk score that was based on key behavioral and psychosocial variables, including mental health, peer substance use, and sport participation. After standardising and aggregating all variables into a single risk index using weighted normalisation informed by the MCDA framework. The resulting continuous risk scores were then stratified into three groups using percentile based thresholds: individuals at or below the 33rd percentile were classified as low-risk, those between the 33rd and 66th percentile as medium-risk and those above the 66th percentile as high-risk. The methodology guarantees data-driven, distribution-sensitive classification and consistency across analyses. Influence and low mental health, whilst the presence of protective factors (sport participation) seems less common within high-risk profiles. The subgroup analyses also reveal that the exposure to the intervention is not a significant disruptor of these risk configurations. These findings are confirmed in Figure 4 (advanced analytical visualisations, such as co-occurrence patterns and model-based interpretation), where substance-related behaviours co-occur, whereas protective variables show inverse relationships. Notably, the predictor impact analyses have identified mental health and peer influence as the most predictive determinants of substance use, with intervention participation, team sport, and gender playing a relative role in predicting substance use.

Figure.4 Risk Patterns, Behavioral Associations, and Determinants of Substance Use

Comentado [AG11]: The methodology does not explain how the low-, medium-, and high-risk categories were constructed.

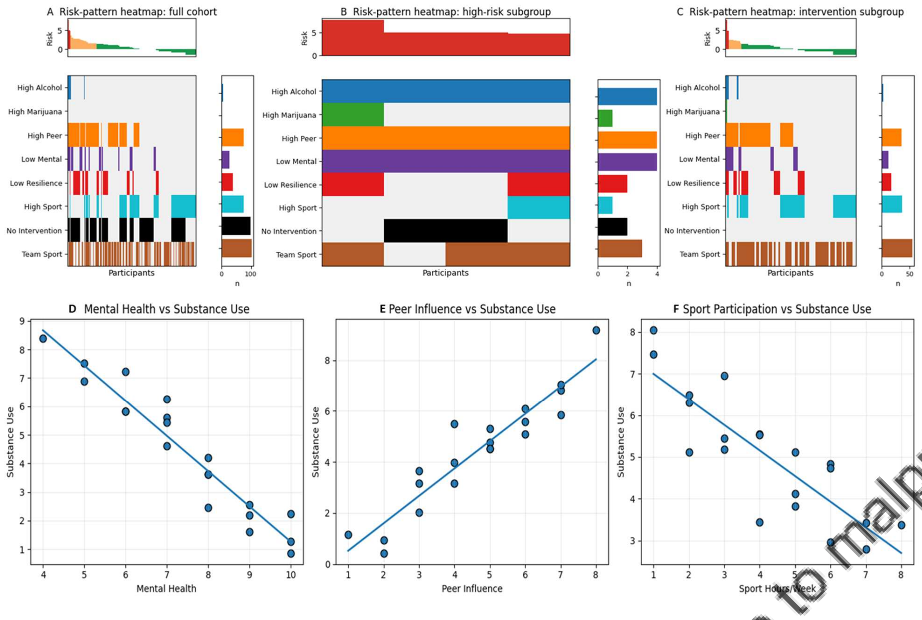

Figure 5 (risk distribution, summary metrics, and group profile comparisons) demonstrates the validity of the developed risk framework, with substance use increasingly prominent across low-, medium-, and high-risk groups. The distribution of composite risk scores shows that although the majority of people are in the lower-risk group, a significant number are in the higher vulnerability group. Also, the connection between sport participation and mental health suggests an indirect, situational protective impact. Comparisons of group profiles indicate small changes among intervention participants, though these differences are not large enough to demonstrate a significant independent effect of the intervention. Combined, these statistics continue to indicate that psychosocial and behavioral interrelations, such as mental health and peer influence, are the primary factors of substance use, and not simply the exposure to interventions, which explains why multidimensional prevention measures should be implemented**.**

Figure.5 Risk Distribution, Behavioral Associations, and Group Profiles in Substance Use Analysis

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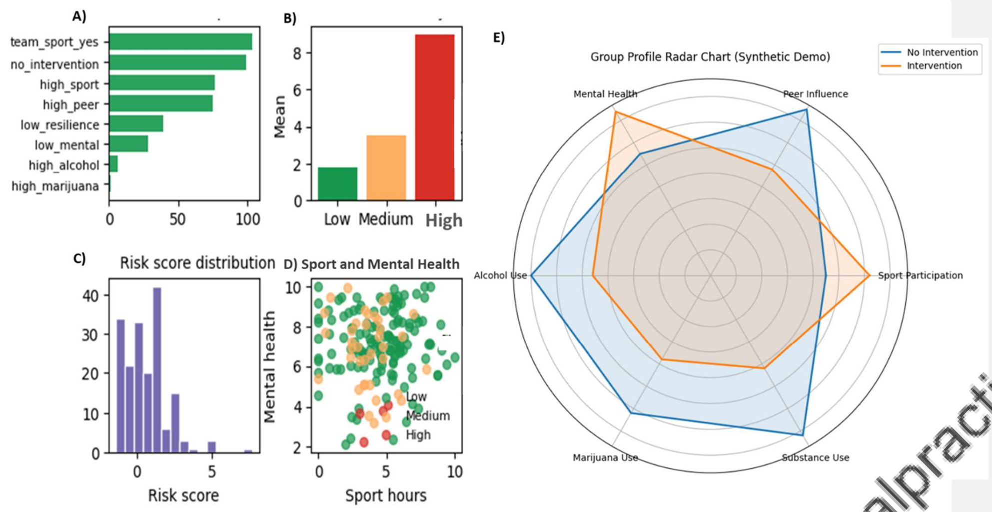

Conclusions

The paper introduces a new, integrated approach to assessing sport-based substance-use prevention programs, grounded in causal inference, machine learning, and multi-criteria decision-making within a dynamic, adaptive framework. The results provide valuable insight into the factors that determine substance use and how prevention interventions could work. In all the possible analytical methods, the psychosocial elements, in particular, mental health and resilience, became the most significant factors of substance-use behaviour. These findings underscore the central importance of internal protective processes and imply that purely behavioural or structure-only-based interventions might be inadequate.

The moderate outcomes of sport participation suggest that engagement in sport may help reduce substance use, though its effectiveness depends on contextual factors and individual characteristics. The lack of a notable direct outcome from participation in the intervention underscores the complexity of prevention outcomes and the roles of implementation quality, program design, and participant characteristics. This observation justifies the need for assessment models that go beyond fixed assessments to include dynamic, data-driven assessments. The new framework can advance the current literature by overcoming some of the limitations of traditional evaluation methods. It enables a more holistic evaluation of intervention efficacy, accounts for heterogeneity in outcomes, and facilitates ad hoc decision-making by combining multiple analytics paradigms. The fact that equity considerations are inclusion criteria further underscores the relevance of implementing this in the context of public health, ensuring that interventions are evaluated not solely on overall efficacy but also on their effects across various population groups. Although the study makes contributions, it is limited by its reliance on a relatively small, somewhat synthetic dataset, which constrains generalizability. Future studies must implement the framework on large-scale real-world data and examine its applicability across different situations and intervention types. To sum up, the research shows that a cohesive, adaptive, and explicit assessment method may play a significant role in improving the efficacy and applicability of substance use prevention programs. The suggested framework provides a clear path to promoting evidence-based policy and practice in public health.

Comentado [AG12]: Physical activity and sport are different concepts

Although the proposed framework is highly analytical and integrative, empirical validation of its components remains limited due to the small sample size and the synthetic nature of its components. These constraints underscore the importance of future applications with large-scale, longitudinal datasets to confirm further that the model is robust, scalable, and policy-relevant.

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