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Predictive modelling links exercise dependence to associated psychological and behavioral risk factors

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ABSTRACT

Exercise Dependence (ED) refers to uncontrollable, excessive exercise with harmful effects on life. This study used machine learning to identify behavioral and psychological factors contributing to ED risk. A multi-step procedure was implemented for model construction and validation, utilizing controlled feature selection and bootstrapping. Data were collected over three time points in diverse contexts (GR2021-22–23), recruiting 1099 participants (707 males, 64.3 %; 392 females, 35.7 %) with an average age of 24.8 ± 7.8 years. Based on the Exercise Dependence Scale-Revised (EDS-R), 5.6 % (n = 62) were classified as "At Risk" of ED, 50.9 % (n = 559) as "Non-Dependent-Symptomatic," and 43.5 % (n = 478) as "Non-Dependent-Asymptomatic." The final model predicted the GR2023 dataset with MAE = 6.90, $R^2 = 0.59$, and RE = 9.08 %. Predictive performance on the GR2022 dataset was MAE = 5.65, $R^2 = 0.79$, and RE = 6.73 %, while performance on the GR2021 dataset achieved MAE = 7.60, $R^2 = 0.58$, and RE = 7.24 %. Perfectionism consistently emerged as the most important predictors, followed by Drive for Thinness, Drive for Muscularity, and sport characteristics. Result generalization was confirmed by a complementary, whole-data analysis. This study establishes a foundation for developing quantitative risk profiles for ED by analyzing multidimensional constructs and their contributions through interpretable machine learning. The methodology offers insights into how personality, psychological, and behavioral dimensions shape risk attitudes and provides robust predictive tools for assessing ED risk in sports contexts.

1. Introduction

Exercise is widely acknowledged as a pivotal factor in promoting health across various populations (Carty et al., 2021; Granger et al., 2017; McPhee et al., 2016) playing a key role in preventing and managing chronic diseases (Pedersen & Saltin, 2015; Ruegsegger & Booth,

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2018; Warburton & Bredin, 2017). While these benefits are well-established, excessive exercise can lead to Exercise Dependence (ED), also referred to as Exercise Addiction (EA), a maladaptive behavioral pattern characterized by excessive training and a loss of control with negative psychological, physical, and social life consequences (Hausenblas & Downs, 2002; Szabo & Demetrovics, 2022). Despite extensive research, ED remains poorly understood regarding its psychological, behavioral, and clinical underpinnings. In clinical literature, ED has been compared to behavioral addictions such as substance-use disorders, based on DSM-5 criteria (APA, 2013), though its clinical validity remains debated. Furthermore, self-report instruments may not fully distinguish between different underlying motivations, limiting their utility in early identification and risk assessment (Lampe et al., 2024; Weinstein & Szabo, 2023). To address this heterogeneity, researchers distinguish between primary ED, driven by addiction-related mechanisms, and secondary ED, driven by symptom-related motives such as weight and body image concerns or motivated by distress reduction or avoidance (Colledge et al., 2020; Egorov & Szabo, 2013; Meyer et al., 2021). Compulsive Exercise (CE) overlaps with secondary ED, representing rigid, obsessive–compulsive patterns characterized by distress, rituals, and obsessive thinking, but excluding classical addiction criteria (Colledge et al., 2020). ED may also operate as a coping strategy for anxiety or emotion regulation (Ceci et al., 2023; A. Sicilia et al., 2020) and personality traits such as rigidity and perfectionism may further shape these exercise patterns and contribute to ED vulnerability (Young et al., 2013). Understanding these distinctions is essential to identify risk and protective factors and tailor predictive models for ED risk.

The multidimensional model proposed by Griffiths (2005) aligns with this framework, characterizing primary ED with six addiction-related components: salience, tolerance, mood modification, withdrawal, conflict, and relapse. Secondary ED is associated with clinical dimensions including eating- and body-image-related pathology, anxiety, and depression (Levit et al., 2018; Weinstein et al., 2015; Zou et al., 2022). Additional mediators of ED may include stress, low self-esteem, and emotional distress, further modulating risk (Gori et al., 2021; Lichtenstein et al., 2018; Pinto et al., 2019). Motivational and personality traits play a critical role in ED. Dysfunctional coping strategies and perfectionism, particularly self-oriented and socially prescribed dimensions, predict ED both directly and indirectly via frustrated needs and introjected regulation, consistent with Self-Determination Theory (Biggs et al., 2024; Hagan & Hausenblas, 2003; Hausenblas & Downs, 2002). Further, maladaptive regulatory strategies longitudinally predict compulsive exercise even after controlling for disordered eating (Goodwin et al., 2012, 2014). In adolescent males, maladaptive perfectionism is linked to heightened Drive for Muscularity (Bratland-Sanda & Sundgot-Borgen, 2012; Hale et al., 2010), while endurance athletes motivated by weight and appearance are more vulnerable than those motivated by health or enjoyment (Hamer & Karageorghis, 2002). Internalized ideals and sociocultural pressures further exacerbate risk, often interacting with body dissatisfaction and the pursuit of an idealized physique (Çakın et al., 2021; Cataldo et al., 2021; De Maria et al., 2023; Godoy-Izquierdo et al., 2023; Minutillo et al., 2024). This interplay can escalate to muscle dysmorphia, promoting excessive exercise and rigid diets that compromise well-being. Developmental and contextual factors also shape ED risk. Loneliness, early involvement in competitive sports, and early emotional deprivation have been implicated in the emergence of addictive exercise patterns (Freimuth et al., 2011; Lukács et al., 2019; Mónok et al., 2012), and these vulnerabilities are evident during adolescence (Bratland-Sanda & Sundgot-Borgen, 2012). Among young adults, compulsive exercise can manifest in distinct subtypes. For instance, Coniglio et al. (2023) identified male college student subgroups with dysfunctional exercise behavior despite outwardly healthy routines. Furthermore, bidirectional relationships among these variables have been observed in recreational exercisers (Alcaraz-Ibáñez et al., 2022), highlighting the complex interplay of personality, coping, and motivational factors. These interactions underscore the need for approaches capable of modeling non-linear and multidimensional relationships. Together, these findings support the view that ED is a complex construct integrating both primary and secondary components possibly overlapping at the behavioral level, and is further shaped by general features such as personality traits, life history, and broader vulnerabilities (Weinstein & Szabo, 2023). Further, research suggests that frequency of exercise alone is insufficient to detect pathology, necessitating the assessment of eating attitudes, body dissatisfaction, and maladaptive motivation. These diverse psychological, motivational, and contextual mechanisms likely contribute to the inconsistency observed in epidemiological findings, particularly in how prevalence rates of ED are estimated across populations. In fact, reported prevalence of ED varies widely (3–43 %), reflecting differences in instruments, cut-offs, sport participation, and cultural context (Bueno-Antequera et al., 2022; Corazza et al., 2019; Costa et al., 2015; Di Lodovico et al., 2019; Granziol et al., 2023; Lichtenstein et al., 2017; Marques et al., 2018; Mónok et al., 2012; Nogueira et al., 2018; Weinstein & Szabo, 2023; Zandonai et al., 2020). High commitment to exercise may not always indicate pathology, particularly among competitive athletes (De La Vega et al., 2016; Smith et al., 2011), emphasizing the need to distinguish adaptive from maladaptive patterns for prevention and early intervention (Szabo et al., 2015). This variability underscores the limitations of traditional analytic approaches, which may struggle to capture the complex, multidimensional interactions underlying ED, highlighting the need for more flexible predictive methods integrating psychological and behavioral variables.

Machine Learning (ML) offers tools to model these complex, multidimensional relationships (Chmait & Westerbeek, 2021; Islam et al., 2023; Palmisano et al., 2022). ML can handle high-dimensional, non-linear data, capturing interactions that traditional regression cannot (Esteva et al., 2019), while explainable AI (XAI) techniques improve interpretability (Lundberg & Lee, 2017). To our knowledge, no prior studies have applied ML to predict ED using multidimensional behavioral and psychological data. In this work, we applied Random Forest regression to variables including body image concerns, perfectionism, and sport-specific factors to develop predictive models of ED risk. This approach allows the identification of non-linear interactions and generation of interpretable risk profiles, supporting prevention and early detection of harmful exercise patterns.

Our aims were to (1) identify psychological and behavioral dimensions contributing to ED risk within a predictive framework, (2) model non-linear interactions among these factors, and (3) highlight potential risk phenotypes for future research. Using multiple datasets, we implemented a robust pipeline for model selection, validation, and cross-sample generalization. By integrating XAI, we enhanced interpretability, allowing the identification of relevant risk aspects and supporting the development of interpretable, clinically relevant ED profiles.

2. Methods

2.1. Participants and procedure

In this observational study, 1099 participants completed the questionnaire. There were more male (n = 707; 64.3 %) than female (n = 392; 35.7 %) participants in the overall sample and the average age (years ± SD) was 24.8 ± 7.8 (males: 25.4 ± 8.1; females: 23.6 ± 7.4). In terms of competitive level, 535 athletes (48.7 %) participated in competitive sports, while 564 athletes (51.3 %) were involved at a non-competitive level. Among competitive athletes, 379 (70.8 %) were male and 156 (29.2 %) were female. In the non-competitive group, 328 (58.2 %) were male and 236 (41.8 %) were female. With respect to sport type, 570 athletes (51.9 %) were engaged in individual sports, and 529 (48.1 %) participated in team sports. Of those in individual sports, 328 (57.5 %) were male and 242 (42.5 %) were female, whereas among team sport athletes, 379 (71.6 %) were male and 150 (28.4 %) were female. Regarding sport level, 170 athletes (15.5 %) were classified as élite (training more than four days per week), 713 (64.9 %) as amateur (training two to three times per week), and 216 (19.6 %) as recreational (training one to two times per week). In the élite group, 118 (69.4 %) were male and 52 (30.6 %) were female. Among amateurs, 465 (65.2 %) were male and 248 (34.8 %) were female. In the recreational group, 124 (57.4 %) were male and 92 (42.6 %) were female (for details see Table 1 in Result). We collected data in different locations and at different times: 2021 in Italy and Spain (GR2021 n = 582), 2022 and 2023 in Spain (GR2022 n = 330; GR2023 n = 187) (for details of all variable data descriptive statistics for whole sample and grouped by biological sex (see Table 1 in Supplementary materials). All participants were recruited through social media platforms by convenience sampling (e.g. Facebook, Instagram, and Twitter). They answered the survey in online format through the Google Forms® platform. Participation was voluntary (age eligible was over 18 years), without any incentive or remuneration. Snowball sampling was also used to increase the number of participants. In particular, participants were asked to send the survey link to other people who exercised after completing the survey. Data collection was anonymous, ensuring maximum data confidentiality. Prior to the start of the survey, participants provided informed consent. The study procedures were carried out in accordance with the Declaration of Helsinki (Association, 2014). All subjects were informed about the study and all provided informed consent. The X Committee approved the study (n. XXX).

Table 1
Characteristics of overall participants.

Variable	Total	Male	Female
Participants (n) (%)	1099 (100)	707 (64.3)	392 (35.7)
Age (mean years ± SD)	24.8 ± 7.8	25.4 ± 8.1	23.6 ± 7.4
Weight (kg)	69.7 ± 13.0	75.5 ± 11.3	59.3 ± 8.8
Height (cm)	174.1 ± 10.1	179.3 ± 7.6	164.8 ± 6.9
BMI	22.8 ± 2.8	23.4 ± 2.7	21.8 ± 2.7
Type of Sport (n) (%)		328	242
Individual	570 (51.9)	(57.5)379	(42.5)150
Team	529 (48.1)	(71.6)	(28.4)
Year practice (years ± SD)	11.1 ± 8.2	12.8 ± 8.6	8.1 ± 6.3
Level of Sport (n) (%)			
Élite	170 (15.5)	118 (69.4)	52 (30.6)
Amateur	713 (64.9)	465 (65.2)	248 (34.8)
Recreational	216 (19.6)	124 (57.4)	92 (42.6)
Competitive (n) (%)	535 (48.7)	379 (70.8)328	156 (29.2)236
Non-Competitive (n) (%)	564 (5.3)	(58.2)	(41.2)
EDS-R (n) (%)		35	27
AR	62 (5.6)	(56.5)346	(43.5)213
NDS	559 (50.9)478	(61.9)325	(38.1)153
NDA	(43.5)	(68.0 %)	(32.0 %)
EDS-R Total (mean values ± SD)	60.2 ± 16.8	60.5 ± 16.0	59.7 ± 18.3
MIPS Total (mean values ± SD)	40.4 ± 9.1	40.6 ± 8.5	40.1 ± 10.0
DFM Total (mean values ± SD)	37.8 ± 14.2	40.0 ± 14.3	33.9 ± 13.2
DFT Total (mean values ± SD)	14.7 ± 8.2	12.6 ± 6.9	18.7 ± 8.9
Supplements use (N) (%)	264 (24.0)	193 (73.1)	71 (26.9)
Analgesics use (N) (%)		358	219
Last 12 month	577 (52.5)	(62.0)258	(38.0)177
Last 30 days	435 (39.6)	(59.3)	(40.7)
Nicotine use (N) (%)	528	321	207
Last 12 month	(48.1)312	(60.8)191	(39.2)121
Last 30 days	(28.4)	(61.2)	(38.8)
Alcohol use (N) (%)	969	642	327
Last 12 month	(88.2)794	(66.2)530	(33.8)264
Last 30 days	(72.3)	(66.8)	(33.2)

Note: EDS-R: Exercise Dependence Scale- Revised; MIPS: Multidimensional Inventory of Perfectionism in Sport; DFT: Drive For Thinness: DFM: Drive For Muscularity; PEAS: Performance Enhancement Attitude Scale.

2.2. Measures

2.2.1. Exercise dependence scale- revised (EDS-R)

ED was measured using the Exercise Dependence Scale-Revised (EDS-R) (Downs et al., 2004); Italian version (Costa et al., 2012); Spanish version (Sicilia & González-Cutre, 2011). The EDS-R consists of 21 items scored on a 6-point Likert scale, ranging from 1 (never) to 6 (always). It comprises seven 3-item subscales that reflect the seven symptoms of ED based on the DSM-V (APA, 2013) criteria for substance dependence: tolerance, withdrawal, intention effects, lack of control, time reduction in other activities, and continuance. Its interpretation can be done quantitatively using the total score, a higher score being associated with greater ED symptoms. For a qualitative interpretation qualitative, those who obtained scores of 5 or 6 in at least 3 of the subscales were classified as "at risk of exercise dependence" (AR); with scores of 3 or 4 in at least 3 of the subscales were classified as "non-dependent symptomatic" (NDS); If they did not meet the above requirements, they were classified as "non-dependent asymptomatic" (NDA). For the Italian version, Costa et al., (2012) reported that confirmatory factor analyses supported a good fit for the hypothesized seven-factor model of the EDS-R, with adequate internal consistency and criterion validity demonstrated through significant correlations between all subscales and exercise frequency. Regarding Spanish version, Sicilia & Gonzalez-Cutre (2011) study found support for both a first-order seven-factor model and a higher-order model of the Exercise Dependence Scale-Revised (EDS-R), with invariance across age groups, good construct validity indicated by inter-subscale correlations, acceptable internal consistency ($\alpha > 0.70$ for most subscales), and adequate temporal stability. In our sample, the EDS-R showed a general Cronbach's α of 0.9 with the total score (95 % CI = [0.89, 0.91]). For the abstinence sub dimension, α was 0.87 [0.86, 0.88]; for continuity 0.81 [0.83, 0.84]; tolerance 0.87 [0.86, 0.88]; control 0.83 [0.81, 0.85]; reduction of other activities 0.48 [0.42, 0.52]; and time 0.83 [0.82, 0.85].

2.2.2. Multidimensional Inventory of Perfectionism in sport (MIPS)

Perfectionism was measured using the short version of the MIPS (Multidimensional Inventory of Perfectionism in Sport) questionnaire, which is composed of 10 items, five of which captured striving for perfection (e.g. "I have the desire to do everything perfectly"), and the remaining five items captured negative reactions to imperfection (e.g. "I feel completely furious if I make mistakes"). The response scale was Likert-type and ranged from never (1) to always (6). The total score is obtained by adding the score for striving for perfection and the score for negative reactions to imperfection (Stoeber et al., 2007; Italian version: De Maria et al., 2021, 2023; Spanish version: Pineda-Espejel et al., 2017). For the purpose of the analysis, we used a total score. A confirmatory factor analysis conducted on a large sample of athletes supported the factorial validity of the MIPS and its use in measuring sport-related perfectionism (Madigan, 2016), while the Italian validation study confirmed its psychometric and construct validity, also highlighting the key role of the personal components of perfectionism (De Maria et al., 2021). In our sample, the MIPS general score showed a Cronbach's α of 0.88 (95 % CI = [0.87, 0.89]). The striving for perfection sub dimension showed an α of 0.90 [0.89, 0.91], whereas the negative reaction to imperfection sub dimension showed an α of 0.89 [0.88–0.90].

2.2.3. Drive for thinness (DFT)

DFT was measured using a subscale of the Eating Disorder Inventory-2 (EDI-2) consisting of 7 items measuring thinness obsession for thinness. Each theme is scored on a 6-point Likert-type scale (1 = never, 6 = always), and a total score is obtained with the sum of all themes. A higher score is associated with a higher obsession with thinness (Italian version: Zelli et al., 2010; Spanish version: Magallares, 2016). The Drive for Thinness subscale of the EDI-2 has demonstrated good reliability and validity across different cultural adaptations, including the Italian and Spanish versions (Zelli et al., 2010; Magallares, 2016), and effectively measures obsession with thinness through a 7-item, 6-point Likert-type scale, with higher scores indicating greater preoccupation with thinness. In our sample, the DFT showed a general Cronbach's α of 0.88 (95 % CI = [0.87, 0.89]).

2.2.4. Drive for muscularity (DFM) scale

DFM was evaluated through 15 items measuring attitudes about muscularity and the desire to be more muscular. Each item is scored on a 6-point Likert-type scale (1 = never, 6 = always). It is interpreted on a continuous basis through the total score, with a higher score being associated with a greater obsession with muscularity (McCreary, 2007; Italian version: Zelli et al., 2010; Spanish version: Sepulveda et al., 2016). The DFM has demonstrated strong psychometric properties, including good internal consistency, test–retest reliability, and evidence of construct validity, making it a reliable and valid tool for assessing individuals' preoccupation with muscularity (McCreary et al., 2004). In our sample, the DFM showed a general Cronbach's α of 0.89 (95 % CI = [0.88, 0.9]).

2.3. Data analysis

We employed a multi-step cross-dataset combinatorial procedure for model construction and validation based on controlled feature selection and bootstrap. Given the three datasets described above, the procedure was iteratively applied to combinations of datasets, i.e. two out of three datasets used for training and the remaining left-out dataset used for testing. For each dataset combination, a first step of feature selection was employed. We employed Pearson correlation between the outcome variable and the numerical candidate predictors, and Wilcox test for binary features. Features with Bonferroni corrected significant associations were retained, except for biological sex, which was always included in the selected features of this first phase as a variable of interest and given sample biological sex imbalance. Afterwards, a bootstrap procedure was repeated 5000 times, randomly selecting (without repetition) the 80 % of internal data for model training. In this internal evaluation phase, Random Forest Feature Importance (Mean Decrease in Impurity) was computed and aggregated over each loop to improve stability. At the end of the internal loop, features with aggregated importance above the 25th percentile were retained and used to provide an unbiased evaluation of the resulting model over the external test set. After testing all the datasets combinations, only common selected features were isolated and a single final model was trained and tested again over each train-test dataset combination. This step guaranteed the evaluation of generalization to different samples, as well as performance coherence between simpler and more complex models. For each dataset combination, model performance metrics were computed over the left-out test set only. Therefore, the analysis was robust at the sample-level. Performance metrics included Mean Average Error (MAE), R^2, and the Relative Error (RE). Ultimately, SHapley Additive exPlanations (SHAP) were employed to improve model interpretation and to derive and discuss dimensions associated with increased or decreased risk profiles across the different conditions. This procedure allowed robust model development and variable selection, as well as improved result interpretation, by producing a common set of features to be evaluated over dataset combinations. However, as a final complementary step, we assembled the three datasets and included our validation procedure in an external 5-fold cross-validation, in order to evaluate model performance over the whole data and enable feature comparison between the two conditions. In fact, despite being rigorous, our approach included only common features among dataset combinations, potentially masking more general associations in the data. Further, this additional analysis allows the comparison of model performance over the two conditions, strengthening the possibility to evaluate result generalization. During each step of predictive modeling, data were standardized considering train elements only, to avoid data leakage. The analysis was performed using Python-3.6.9 and the scikit-learn library.

3. Results

3.1. Participants

Table 1 shows all variable data descriptive statistics for overall participants.

3.2. Predictive model

The initial feature set in our data analysis plan consisted of 27 variables. Numerical variables included: Age (years), Weight (Kg), Height (cm), Body Mass Index (BMI), Level of Sport (Élite, Amateur, Recreational), MIPS Total, DFM Total, DFT Total, and Years of practice (years). Base categorical variables included: Biological Sex, Competitive, Type of Sport (Individual, Team), and Supplements use. Specific categorical variables included the Alcohol and Nicotine use (categorical information about the assumption in the last 12 months and 30 days were included), Analgesics use. For Alcohol and Nicotine variables, information about use before, during (except for alcohol), and after training.

Biological Sex was automatically selected as candidate predictor for the internal model validation, and eventually excluded only if not selected by RF importance.

The combination of GR2021 and GR2022 datasets for train predicted the GR2023 dataset with MAE = 7.96, R^2 = 0.55, and RE = 10.45 %. Selected variables included: Level of sport, Type of sport, Competitive, Drive For Muscularity, Drive For Thinness, and Perfectionism.

The combination of GR2021 and GR2023 datasets predicted the GR2022 dataset with MAE = 6.19, R^2 = 0.75, and RE = 7.37 %. The selected features were the same as the previous combination.

Finally, the combination of GR2022 and GR2023 datasets predicted the GR2021 dataset with MAE = 7.61, R^2 = 0.58, and RE = 7.24 %. The model included just Level of sport, Drive For Muscularity, Drive For Thinness, and Perfectionism.

Features retained for the external validation were therefore the minimal set selected in the last combination.

The final model predicted the GR2023 dataset with MAE = 6.90, R^2 = 0.59, and RE = 9.08 %.

Predictive performance over the GR2022 dataset were MAE = 5.65, R^2 = 0.79, and RE = 6.73 %.

Finally, performance over the GR2021 dataset was MAE = 7.60, R^2 = 0.58, and RE = 7.24 %.

The average global relative error of the final model over the three test sets was RE = 7.68 %. The analysis supported the stability of reduced models in predictive performance, as well as feature generalization for all the tested conditions. Model fits are reported in Fig. 1.

Feature importance computed through the SHAP analysis highlighted the main role of Perfectionism, followed by Drive For Muscularity, Drive For Thinness, and Level of Sport. Moreover, SHAP coefficients underscored a specific risk profile for developing ED. In particular, higher levels of Perfectionism, Drive For Muscularity, Drive For Thinness, and Level of Sports were associated with the highest scores in ED. The amatorial level was already associated with a positive risk for ED, as well as higher Level of Sport. The SHAP analysis results are reported in Fig. 2.

3.3. Complementary analysis

5-fold cross-validation was performed over the whole dataset to compare model performance and feature selection, and to evaluate result generalization. Over the five folds, MIPS Total, DFM Total, and DFT Total were consistently selected as the most important features. The Level of Sport and Competition were also selected in all folds. Additionally, Type of Sport was selected in two out of five folds. Finally, Biological Sex and Supplements use were selected in one fold out of five. Results indicated coherent model performance in evaluation metrics, with MAE = 7.80 (0.26), R^2 = 0.60 (0.05), and RE = 8.83 % (1.12). The

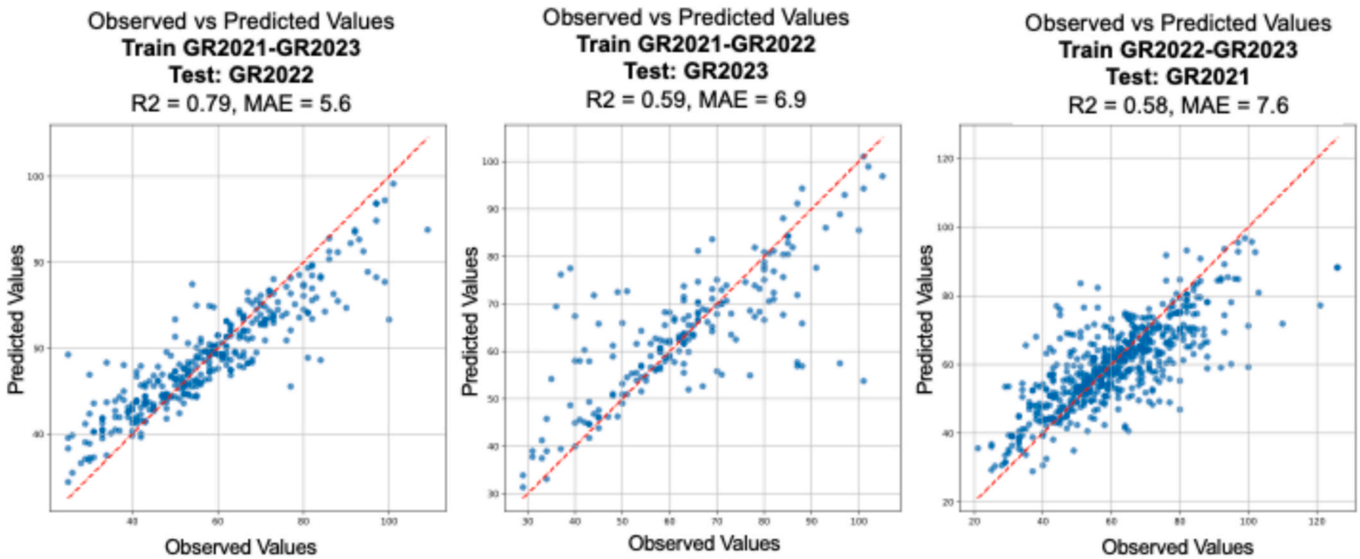

Fig. 1. Model predictive performance over the test sets. Note: MIPS: Multidimension Inventory of Perfectionism in Sport; DFT: Drive for thinness: DFM: Drive for muscularity; SHAP: SHapley Additive exPlanations. The SHAP plot shows the contribution of features to the model's predictions, with each dot representing a sample positioned along the x-axis according to its SHAP value. SHAP values quantify features' impact on prediction: higher positive values increase the prediction, negative values decrease it. Features are ordered vertically by importance. SHAP values' magnitude directly reflects the contribution size: a SHAP value of 0 indicates no influence, positive or negative values quantify how much the feature shifts the model's prediction from the baseline. Patterns in the distribution reveal whether high or low feature values consistently drive predictions.

same variables that predicted ED in the initial validation consistently emerged as the most important predictors when considering the whole data in the validation procedure with the same priority. Additionally, the complementary analysis revealed that being male, engaging in a competitive sport, and using supplements may beis associated with increased risk of ED, at least for some sub-groups. The analysis of SHAP plots also indicated that, despite an overall positive effect of the use of supplements, its distribution appears to be non-linear, with a cluster of subjects displaying a negative association.

4. Discussion

The aim of this work was to identify behavioral and psychological risk factors linked to ED through a robust data-driven approach employing machine learning techniques over three different samples. We performed a controlled features selection step to train predictive models on different combinations of datasets. Performance was evaluated over the left-out dataset to extracted unbiased metrics. Using a nested bootstrap procedure we ensured the evaluation of feature stability across different subsamples of training data. Further, using combinations of datasets allowed the evaluation of generalizability to different contexts, as well as feature stability. Finally, we employed a technique for explainable machine learning to further interpret our results in terms of sign and strength of the association between selected predictors and the outcome variable.

Participants showed a 5.6 % of risk of ED, consistently with previous studies (Costa et al., 2015; Marques et al., 2018; Zandonai et al., 2020). Our analysis linked four variables with ED across all the tested combinations. Notably, feature importance for all the experiments resulted to be stable and coherent with respect to feature contribution. The most important contribution resulted to be perfectionism as a psychological trait. Scoring higher in perfectionism is linked to an increased risk of developing ED. Perfectionism refers to a complex psychological dimension with at least two axes involving concerns and strivings (Stoeber, 2017), with implications at both the personal and interpersonal levels (Hewitt & Flett, 1991). Therefore, our results are in line with evidence linking multidimensional perfectionism as a risk factor for ED (Biggs et al., 2024).

The second and third associated risk factors were drive for muscularity and drive for thinness. Results suggest that these body-oriented dimensions have an important contribution independently from the one of perfectionism (Tod & Edwards, 2015). Research indicates that individuals with a heightened drive for muscularity are more exposed to the risk of developing ED, often as a means to attain an idealized physique (Hale et al., 2010). Similarly, the drive for thinness has been widely associated with excessive exercise patterns, particularly among individuals who internalize societal pressures for leanness and body image concerns (Griffiths et al., 2018). Finally, the level of sport participation also contributed as a more environmental, transversal factor. Athletes competing at higher levels of sport activity showed an increased risk of scoring high in ED, suggesting that contextual factors, such as performance pressure, structured training regimens, and competitive environments, may contribute to the development of ED behaviors (Di Lodovico et al., 2019). This aligns with findings indicating that elite and amateur athletes experience greater pressure to maintain rigorous exercise routines, increasing their vulnerability to ED (Nogueira et al., 2022). Notably, only the recreational level appears to be associated with a reduced risk of ED, whereas amateur athletes already show an increased contribution to dependence risk, even if lower than professionals (De La Vega et al., 2016). This trend suggests that higher levels of sport involvement, often characterized by external performance expectations and long-term commitment, may foster ED (Guo et al., 2025).

Despite being retained in the first variable selection step, biological sex was then excluded by the second aggregated feature selection step. However, further research should assess the contribution of biological sex to the dimensions of muscularity and thinness. Interestingly, recent research highlighted a muscular component in pathological exercise common to both men and women (Dreier et al., 2021). Coherently, our analysis, suggests that these dimensions may move quite independently with respect to gender concerning their contribution to dependence risk. Furthermore, the role of competition and individual vs. team sport emerged, although not consistently throughout dataset combinations. Studies have highlighted that team-sport athletes may be at a lower risk compared to individual-sport athletes, as team environments often provide greater social support, which can mitigate compulsive

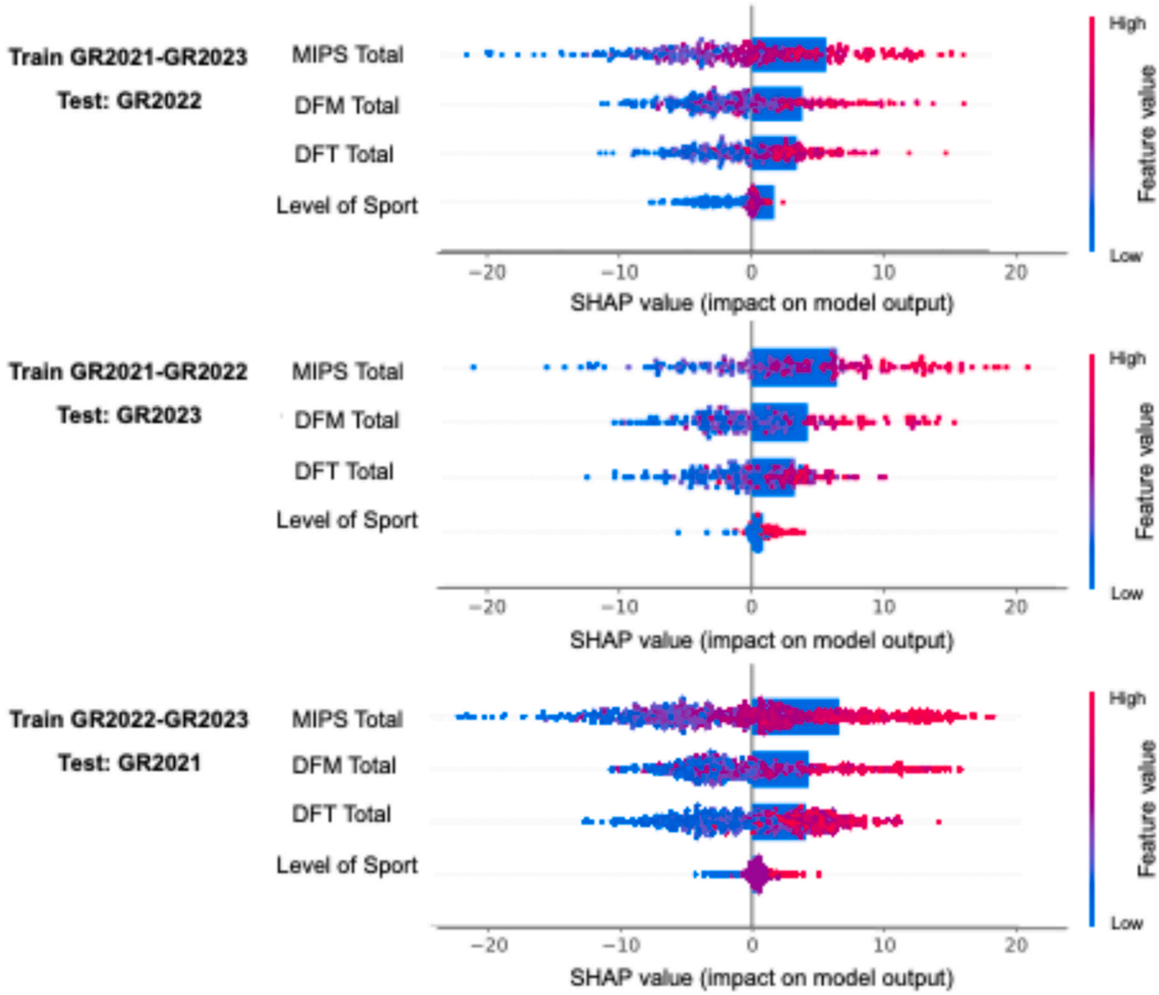

Fig. 2. SHAP plots for feature contributions on ED over the test sets. Note: MIPS: Multidimensional Inventory of Perfectionism in Sport; DFT: Drive For Thinness: DFM: Drive For Muscularity; SHAP: SHapley Additive exPlanations. The SHAP plot shows the contribution of features to the model's predictions, with each dot representing a sample positioned along the x-axis according to its SHAP value. SHAP values quantify features' impact on prediction: higher positive values increase the prediction, negative values decrease it. Features are ordered vertically by importance. SHAP values' magnitude directly reflects the contribution size: a SHAP value of 0 indicates no influence, positive or negative values quantify how much the feature shifts the model's prediction from the baseline. Patterns in the distribution reveal whether high or low feature values consistently drive predictions.

tendencies (Griffiths et al., 2023; Nogueira et al., 2018). Given our robust approach to feature selection and model evaluation, certain variables, such as sport competition level and group vs. individual sport organization were not consistently retained in the final model across cross-validation folds. However, our complementary analysis indicated a recurring association between higher levels of sport competition and increased ED risk when considering the full dataset. Similarly, the distinction between individual and group-based sports also emerged, though less consistently. Notably, these same variables also emerged in our original, non-merged analyses with similarly inconsistent patterns of selection. This variability is an expected outcome of the cross-validation process, which introduces randomness in fold partitioning and applies conservative thresholds to prioritize robustness and generalizability. Nonetheless, the inconsistent selection of these features across folds, as well as their lower importance, may also suggest the presence of subgroups within the data characterized by distinct profiles. In such cases, the model is more likely to highlight broadly shared transversal predictors, while the influence of subgroup-specific variables may be attenuated. These potential subgroups may reflect meaningful distinctions in motivational or contextual factors, such as athletes competing at higher levels of competition or engaged in individual sports, who may be more vulnerable to performance-related pressure, self-imposed standards, or reduced social connectedness. These elements, in turn, could contribute to elevated ED risk within specific psychological or behavioral profiles. Biological sex and the use of supplements were selected in just one fold of the complementary analysis, with reduced importance. Taken together, these results indicate that being male, engaging in a competitive, individual sport, and using supplements may contribute to an increased risk for ED. Interestingly, our XAI framework also allowed the identification of a cluster of subjects showing an opposite pattern with respect to the use of supplements. This further underlines the necessity of employing models able to catch non-linear and interaction relationships such as ML, as well as focusing on phenotyping to identify clusters with differential risk features. These additional variables should be taken with caution given that they were not consistently selected during cross-validation, and their feature importance is lower than those of the more general features emerged in our more conservative analysis.

The complementary analysis further allowed model comparison and strengthened result generalization, showing general coherence with our main analysis and indicating that the main and strongest patterns identified among the combined datasets are consistently found also when considering the whole data. Further, thanks to a less conservative, more general approach, it allowed the identification of additional features that may be linked to ED and may be worth further attention, possibly requiring more focused research efforts. This points out the need for more sophisticated phenotyping techniques such as clustering or the investigation of latent components. Therefore, future research should investigate the specific contribution of these variables as possible behavioral/environmental markers associated with an increased risk of ED also in pre-clinical terms.

To summarize, our results suggest that motivational, psychological, and sport-related factors contribute to the risk of developing ED, particularly through mechanisms linked to body-image, perfectionistic personality trait and sport level, underscoring the importance of including pre-clinical aspects when assessing risk behaviors in athletic contexts. Notably, feature importance analyses highlight perfectionism, as a personality trait, as the main contributor to predicting exercise dependence, followed by drive for muscularity and drive for thinness, along with sport-related characteristics. Perfectionism, consistently emerging as the strongest predictor, seems to suggest that personality traits and motivational dynamics may increase the risk of exercise dependence. In contrast, motivation toward muscularity and, especially, drive for thinness may be more closely associated with secondary exercise dependence. This interpretation reflects ongoing debates in the literature about the boundaries and possible integration between primary and secondary exercise dependence, and underscores the importance of considering both trait-level and motivational factors. Finally, our results also underscore the role of sport-related features, which may represent transversal risk factors for the development of exercise dependence. In line with this, research evidence suggests that, as it is currently defined, exercise dependence may integrate different aspects related to other clinical and non-clinical constructs, as well as relying on self-report instruments that may not only confound different factors (e.g. addictive and instrumental) but also being differentially interpreted based on the target population (e.g. professionals and the general population), therefore possibly not representing a coherent, unique, generalizable construct (Colledge et al., 2020; Szabo et al., 2015). This further underlines the need for precision approaches to unravel potential subclusters in the general population that may exceed in exercising for various potential reasons and mechanisms (Weinstein & Szabo, 2023), including cultural aspects and sport-related features (Wang et al., 2025).

This work is not without limitation, the main one being represented by the cross-sectional measures included. In fact, questionnaires were administered at the same time for both predictors and the outcome variable. Therefore, despite a rigorous predictive evaluation, this analysis could not reveal more in-depth temporal causal relationships between our variables of interest. A longitudinal design could actually shed light on the role of the identified risk factors as temporal precursors for developing ED. Future research should investigate whether the subdimensions of perfectionism specifically contribute to dependence risk. Moreover, despite multiple data sources and times, convenience/snowball sampling has self-selection issues that may limit result generalization.

5. Conclusions

To conclude, this work represents a first step towards the development of quantitative profile risks for ED considering multidimensional constructs and investigating the contribution of each dimension to the final risk through a controlled and interpretable machine learning predictive approach. Such methodology could pave the way to the understanding of how personality, psychological, and behavioral dimensions can contribute to developing risk attitudes, as well as providing numerically solid methods to predict the risk in sport contexts.

Ethical approval

The study procedures were carried out in accordance with the Declaration of Helsinki. All subjects were informed about the study and all provided informed consent. The Research Ethics and Integrity Committee, Vice-rectorate of Research of the Miguel Hernández University of Elche, Alicante, Spain approved the study (DFP.TZ.02.20 – TFM.DFP.TZ.01.20 – TFG.GME.AMPP.FVS.230309 – TFG.GME.AMPP.NCSL.211113).

CRediT authorship contribution statement

Thomas Zandonai: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Giulio Bertamini:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Juan José Lozano:** Writing – review & editing, Methodology, Investigation, Data curation. **Luca Mallia:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Alessandra De Maria:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Federica Galli:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Pablo Monteagudo:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Fabio Lucidi:** Writing – review & editing, Methodology, Investigation, Data curation. **Paola Venuti:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation. **Cesare Furlanello:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Ana María Peirò:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.addbeh.2025.108493.

Data availability

The data that support the findings of this study are openly available in Figshare at: https://doi.org/10.6084/m9.figshare.28417490

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