



ARTICLE



A COMPETITIVE INTELLIGENCE FRAMEWORK FOR PREDICTING PHYSICAL FITNESS OUTCOMES USING DATA ANALYTICS

UM FRAMEWORK DE INTELIGÊNCIA COMPETITIVA PARA PREDIZER RESULTADOS DE APTIDÃO FÍSICA USANDO ANÁLISE DE DADOS

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ABSTRACT

Purpose: This article creates a competitive intelligence framework to determine the results of physical fitness on data analytics. The paper discusses a practical issue that is common to sport organizations, fitness platforms, public-health programs, universities, and clinical exercise services: huge amounts of physical activity and health data are being produced, yet most institutions do not have a system that allows them to convert that data into actionable foresight regarding performance, adherence, and recovery and fitness risk.

Methodology/approach: Study is a synthesis of integrative literature analysis, followed by a simulation-based analysis illustration. A literature review of the recent literature on competitive intelligence, sport analytics, wearables, machine learning, physical activity monitoring, and ethical AI published between 2021 and 2025 was viewed to define the framework, and a literature informed synthetic panel of repeated fitness observations was operationalized in such a way that feature engineering, model benchmarking, calibration assessment, decision translation, and post-deployment drift monitoring could be applied.

Originality/Relevance: The originality of the article is the ability to combine the logic of competitive intelligence with the predictive fitness analytics. The previous research has typically investigated the wearable monitoring, exercise prediction, or sport analytics separately. This paper re-positions physical fitness prediction as an intelligence that can be used to make anticipatory decisions, prioritize resources, intervene at a personal level, and maintain competitive advantage.

Key findings: The model shows that useful fitness prediction is found when fusing physiology, training load, behaviour, recovery, and contextual signals over rolling time windows and assessing them using properties of nested validation. Both boosted-tree and **temporal** models were the best on the discrimination in the analytical illustration, but deployment quality was as well founded on the criterion of calibration, explainability, and drift and intervention prioritization governance.

Theoretical/methodological contributions: The article uses the theory of competitive intelligence in the context of the physical fitness analytics industry and offers a valid model that could be utilized by scholars and managers. It adds a process perspective of how organizations may transform raw data into prospective intelligence, defines critical variables and model options to predict physical fitness, and has a research agenda in future on validation, fairness, interoperability, and human-AI interaction.

Keywords: Competitive Intelligence. Fitness Analytics. Predictive Modeling. Wearable Data. Data-Driven Decision Making.



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RESUMO

Objetivo: Este artigo desenvolve um framework de inteligência competitiva para determinar os resultados da aptidão física a partir da análise de dados. O trabalho discute um problema prático comum a organizações esportivas, plataformas de fitness, programas de saúde pública, universidades e serviços clínicos de exercício: grandes volumes de dados de atividade física e saúde estão sendo produzidos, porém a maioria das instituições não possui um sistema que permita converter esses dados em inteligência acionável para antecipar desempenho, adesão, recuperação e riscos relacionados à aptidão física.

Metodologia/abordagem: O estudo consiste em uma síntese baseada em análise integrativa da literatura, seguida por uma ilustração analítica baseada em simulação. Foi realizada uma revisão da literatura recente sobre inteligência competitiva, sport analytics, wearables, aprendizado de máquina, monitoramento de atividade física e inteligência artificial ética, publicada entre 2021 e 2025, para definir o framework. A partir disso, foi operacionalizado um painel sintético de observações repetidas de fitness, fundamentado na literatura, permitindo a aplicação de engenharia de atributos, benchmarking de modelos, avaliação de calibração, tradução para decisões gerenciais e monitoramento de drift após a implantação.

Originalidade/Relevância: A originalidade do artigo reside na capacidade de integrar a lógica da inteligência competitiva com a análise preditiva aplicada à aptidão física. Pesquisas anteriores normalmente investigaram separadamente monitoramento por wearables, previsão de desempenho físico ou sport analytics. Este trabalho reposiciona a previsão da aptidão física como uma forma de inteligência capaz de apoiar decisões antecipatórias, priorizar recursos, orientar intervenções personalizadas e sustentar vantagem competitiva.

Principais resultados: O modelo demonstra que previsões úteis de aptidão física emergem da integração entre variáveis fisiológicas, carga de treinamento, comportamento, recuperação e sinais contextuais analisados em janelas temporais móveis e avaliados por meio de validação aninhada. Modelos baseados em árvores de decisão aprimoradas (boosted trees) e modelos temporais apresentaram melhor desempenho discriminatório na ilustração analítica. Entretanto, a qualidade de implantação também depende de critérios como calibração, explicabilidade, monitoramento de drift e governança para priorização de intervenções.

Contribuições teóricas/metodológicas: O artigo aplica a teoria da inteligência competitiva ao contexto da indústria de análise de aptidão física e propõe um modelo aplicável tanto para pesquisadores quanto para gestores. O estudo acrescenta uma perspectiva processual sobre como organizações podem transformar dados brutos em inteligência prospectiva, define variáveis críticas e alternativas de modelagem para previsão da aptidão física e apresenta uma agenda de pesquisa futura envolvendo validação, equidade algorítmica, interoperabilidade e interação humano-IA.

Palavras-chave: Inteligência Competitiva. Análise de Fitness. Modelagem Preditiva. Dados de Wearables. Tomada de Decisão Baseada em Dados.



1. INTRODUCTION

Physical fitness is not measured solely by some field tests or even backward reports. Fitness represents a growing range of heterogeneous data streams created by wearables, mobile apps, laboratory data, electronic medical records, self-reports, and contextual sensors offered by the fitness industry to sport, athletics, and other fields, in both contemporary sport and fitness. Such a change has provided a possibility to go to the forward-looking intelligence instead of descriptive monitoring. Organizations can also inquire not about how fit a particular individual is at a particular time, but rather ask what athletes, patients, or users are likely to be better, stagnate, disengage, become overloaded, or underperform in the near future. The strategic importance of predictive thinking is that physical fitness interventions are time-sensitive: decisions made late cost the training cycles, and the interventions can increase the risk of injuries or subsequent dropouts (Watanabe et al., 2021; Bai and Bai, 2021; Ferguson et al., 2022).

The strategic utility of physical fitness prediction has increased with organizations competing in the quality of their performances, retention, health, and personalization of services. Elite sport programs fight over fringe benefits. The companies in the fitness technology sector fight over the users and their conformity. Universities and schools are competing based on development of athletes and their wellbeing measures. There is an indirect competition between health systems and community programs on their efficiency, reach and impact. The common operation issue in all of these environments is that decision makers have never had as much data as they do currently, but they seem to lack a coherent intelligence structure that will explain what they should gather, how they should integrate signals, how they will interpret model results, and what they will do with them (Ranjan and Foropon, 2021; Hassani and Mosconi, 2022; Mantsescu, 2025).

It has been already demonstrated by the literature that data analytics can be used to model physical activity and fitness meaningfully. In recent years, wearable-derived step counts have been associated with the risk of chronic disease (Joensuu et al., 2021), machine learning has been used to predict shifts in shuttle-run performance (Jossa-Bastidas et al., 2021), machine learning has been developed to predict exercise adherence in a digital setting (Master et al., 2022), and deep-learning systems have been developed to classify physical fitness loss in aging populations (Bae et al., 2023). Simultaneously, systematic reviews indicate that the success appears not only to be determined by the choice of algorithms but also by the validity of data, sampling logic, the context of behaviour, interoperability, and trust in digital tools by organizations (Kristoffersson and Linden, 2022; Giurgiu et al., 2023; Rebelo et al., 2023).

With these developments, there is still a great gap. A lot of literature in analytics deals with model accuracy, device validity or sport specific use, but a lot of the literature dealing with competitive intelligence deals with scanning the environment, interpreting it and gaining an advantage in the business world. These streams do not often intersect in a manner that elucidates how organisations need to control data pipelines, priorities of intelligence need, predictive relevance and woven insights into everyday decision-making regarding fitness development. In the absence of such a connection, predictive tools may



not become institutional capabilities, but instead, they may continue to be isolated technical artefacts (Hassani and Mosconi, 2021; Cadden et al., 2023; Krakowski et al., 2023).

The article fills this gap by offering a competitive intelligence model to forecast the physical fitness results by applying data analytics. The article also states that the prediction of physical fitness is not based on a modelling task but a cycle of intelligence. The main assumption is that predictive utility and strategic beneficence can arise when organizations integrate the purpose of intelligence, data management, predictive analytics, and response measures. The article thus aims at three things, the first is to integrate the current knowledge on fitness related data analytics, the second one is to define the key constructs required to interpret the physical fitness prediction in terms of competitive intelligence and finally, to provide an implementable framework that can be adopted by managers and researchers under various institutional contexts.

2. THEORETICAL FRAMEWORK

The framework suggested in this paper has a theoretical foundation on competitive intelligence. Classically, competitive intelligence has dealt with the ethics and orderly gathering, examination, and sharing of information that enhances strategic choices amid a state of uncertainty. In the digital realm, the notion has broadened the competitor surveillance, to incessant sniffing of market, technological, behavioural and operational cues. This development is more applicable in physical fitness environment where competitive advantage is determined by the speed and smartness of organizations to process fast evolving data.

2.1 Competitive intelligence as a data-based capability

Latest academic work has revealed that big data, social media analytics and AI-enabled decision systems are transforming competitive intelligence. Ranjan and Foropon (2021) believe that big data analytics capability cannot be understood as a mere technical resource, but rather as a mechanism by which organizations generate competitive intelligence by translating disseminated information into coherent foresight. Similar findings are shown by Hassani and Mosconi (2022), who argue that all phases of intelligence planning, collection, analysis, and dissemination should be integrated with analytics instead of being added as an afterthought at the end of the process. Their work can be particularly helpful in physical fitness analytics since they predict the process integration: the intelligence becomes valuable only when the information flows are oriented towards organizational routines.

In the physical fitness world, the concept of competition is not limited on the direct market competition. Performance superiority, wearable platform performance, athlete progression, participation and health impact compete with a professional club, university sports unit, and a wearable platform, respectively. In both instances, benefit lies in the capability to perceive the emergence of changes more promptly than the rest



and take action in a more efficient way. Fitness competitive intelligence should therefore be considered to be the ability to detect useful messages on current and future fitness conditions, frame their meaning, and take timely action.

This is supported by the literature on AI and competitive advantage. As demonstrated by Krakowski et al. (2023), AI can shift the advantage sources by replacing the value of still resources with the capabilities to learn and to predict better with the help of data. Cadden et al. (2023) further contend that analytics can be strategically productive when companies develop knowledge-integration habits where various data resources can be used to guide innovation and competitive positioning. In the context of physical fitness, this implies that the value of data does not emerge out of the number of sensors used but out of how well the organization uses physiological, behavioural and contextual evidence to make a decision related to training load, recovery, adherence and risk.

Due to this reason, competitive intelligence lens will be more suitable than a technical analytics lens. A technical lens is concerned with variables and models whereby the performance measures include variables like accuracy or area under the curve. These issues are contained in competitive intelligence lens, but they would also pose the question of whether the model provides an answer to a strategically relevant question, whether the output can be interpreted by coaches or managers, whether the prediction is timely to alter an outcome, and whether the organization has response procedures associated with the prediction. The framework that this article has suggested looks at analytics as a component of a larger intelligence cycle.

The improvement of physical fitness is multidimensional. When predictive systems work to decrease the fitness to one score, they are weak, and when they model fitness as a portfolio of interrelated states and trajectories, they are strong.

2.2 Intelligence objects as the results of physical fitness

Practically, the results of physical fitness could be cardiorespiratory fitness, muscular strength, muscular endurance, flexibility, speed, agility, body composition, recovery status, consistency of attendance, adherence to exercise, preparedness to injury, and risk of long-term health. Evidence on adolescence and aging, as well as clinical populations, demonstrates that the results are influenced by a combination of demographic, behavioural, and physiological variables instead of the independent variables of exercise (Liu, 2021; Bae et al., 2023; Singh et al., 2024). This fact substantiates our assumption that fitness prediction aims both at the present and prospective direction.

Literature also reveals that outcome choice is situational in an organization. At the youth or education level, predictive models can be more oriented towards development in the shuttle-run performance, motor competence, or consistent participation (Joensuu et al., 2021). Adherence or the probability of dropout can be the most strategic target in consumer fitness models since adherence allows mediating



downstream fitness benefits (Jossa-Bastidas et al., 2021). The focus in the clinical or public-health context can be on the steps, moderate-vigorous exercise, strength activity adherence, or reduction of disease risks related to physical activity patterns (Hyde et al., 2021; Master et al., 2022). Ready, External load, Locomotor, fatigue, and Return-to-play can be used in monitoring in elite sport (Rebelo et al., 2023; Nassis et al., 2023; Olsen et al., 2025).

One of the competitive intelligence perspectives levels proposes that physical fitness results should fall into three categories in the organizations. The first one is performance outcomes, such as the measurable speed, endurance, strength, power, and functional capacity improvements. The second type is sustainability outcomes, including adherence, recovery quality, and load tolerance, as these decide whether it is possible to sustain improvements. The third one is strategic-risk outcomes, comprising non-response to training, probable decline, early dropout, or health deterioration. These categories do not exclude each other; the categories assist managers to establish the most important predictions to make in making certain decisions.

The classification is significant due to the fact that predictive analytics can be useful based on the decision horizon. Others are short term when determining who to have a lighter training day. Others lie in the medium term, i.e. predicting the users who will be likely to disengage in one month. Other longitudinal are still other estimations, e.g., estimating the activity trajectories that are linked to cardio metabolic risk in a series of years. The selected prediction horizon determines both the data needed, the rate at which models are refreshed, the allowance of false positives and the severity of human supervision.

The second conceptual problem is that of data. Predictive fitness intelligence is based on data ecosystems, as opposed to a single repository.

2.3 Analytics, wearables and predictive modelling

According to current studies, physical activity and fitness analytics are based on an increasingly broader range of types of data: wearable accelerometer, heart rate, inertial motion, GPS traces, training load logs, volume of resistance training, attendance records, sleep signal, survey data, psychological, medical history, body composition data, environmental factors and device interaction patterns (Kristoffersson and Linden, 2022; Shei et al., 2022; Liang et al., 2024). Continuous monitoring has further increased predictive opportunity and the complexity of governance that the periodic assessment did.

Wearables are particularly significant since they generate high-frequency behavioural and physiological measurements in the natural world. According to systematic reviews, wearables have the potential to facilitate behaviour change, enhance physical activity, and offer valuable information to monitor health and performance, yet they differ in their accuracy in different situations, measures, and populations (Ferguson et al., 2022; Wang et al., 2022; Giurgiu et al., 2023). Due to this reason, the output of the device must not be viewed as a self-evident truth but must be



viewed as an input that needs validation, calibration, and interpretation in the context of what it is.

The predictive work has come to focus on machine learning due to their tendency of nonlinearity, multimodality and longitudinality of most fitness datasets. Regression models, tree-based, neural networks, deep learning, and ensemble models have been used to forecast fitness progression in adolescence, categorize sarcopenia-related loss of fitness, predict exercise intensity, and predict adherence patterns based on app interactions (Joensuu et al., 2021; Jossa-Bastidas et al., 2021; Bae et al., 2023; Biró et al., 2023). Recent sports studies also indicate that there is increasingly the use of AI in optimising performance, biomechanics, readiness, and injury-related inference (Cossich et al., 2023; Zhou et al., 2025; Souaifi et al., 2025).

However, predictive utility is not only based on the sophistication of algorithms. Some of the aspects such as feature engineering, missing-data strategy, temporal granularity, sensor synchronization, class imbalance treatment, and external validation tend to dictate the practical reliability of a model. Indicatively, predictive models of fitness deterioration based on a single cross-sectional observation can do well with a limited sample and fail to extrapolate to normal work conditions. In comparison, longitudinal behaviour, contextual covariates and repeated outcome measure models can contribute greater decision value despite being less mathematically complex.

Hence, data analytics should be viewed as a pipeline within competitive intelligence framework with four analytic accountabilities, which include: signal detection, prediction, explanation, and monitoring. Signals are detected and identify variables to pay attention to. The future states or the probability is estimated by prediction. Explanation is used to clarify on which factors the forecast is being driven and whether the output is credible. Monitoring is used to test how the model can be stable as the population, devices, behaviours, and environments vary. The wider perspective is especially required when predictions are involved in individualized training prescriptions or when scarce support resources are being distributed.

Since physical fitness prediction entails individual, behavioural and in many cases, health related data, governance is not a periphery issue. It is an essential requirement of the validity and sustainability of intelligence systems.

2.4 Governance, explainability and adoption

According to the recent reviews, interoperability, data ownership, privacy, fairness, model drift, and explainability have remained persistent issues of digital sport and health systems (Petek et al., 2023; Kim et al., 2025; Zhou et al., 2025). Such problems are further amplified as organizations integrate wearable information with health records, attendance information or commercial platform information. An accurate, but opaque, model can be rejected by coaches, clinicians or users due to the lack of understanding of what motivated the generation of a prediction and how this prediction needs to influence action.



Ethical governance is also important since predictive systems are capable of recreating bias. When training data favors one group of people in terms of age, sex, sport, or fitness level, the model will not be effective in the others. In case adherence models do not reward people, who do not attend facilities regularly or have irregular schedules, the system can do a disservice of declaring structural disadvantage low motivation. Useful and fair predictive intelligence needs concern with data provenance, subgroup validation, open communication, and human review threshold therefore (Kim et al., 2025; Olthof and Davis, 2025).

Moreover, the institutional adoption is based on workflow fit. Black-box probability is seldom the quantity that coaches and managers require, but they need decision-ready intelligence: e.g., does a person need a screening conversation, a different form of training microcycle or a recovery intervention. This implies that governance must incorporate the escalation procedures, definition of accountability, and post-decision auditing. Precisely, fitness intelligence system quality is both statistical and organizational.

3 METHOD

The current study employs an integrative conceptual approach that is supplemented with a simulation-based analytical example to develop a theoretically base yet practice-oriented framework. This was to not only synthesize dispersed knowledge, but also to demonstrate how a competitive-intelligence architecture can be operationalized in a technical way to make predictions that can be used to predict fitness. This hybrid design suits cases in which the issue is interdisciplinary and organizations require not individual technical results but a conceptual clarity plus an analytics logic that can be implemented.

The literature base was determined on the five overlapping areas, which comprised competitive intelligence and business analytics; wearable and sensor-based physical activity monitoring; machine learning predicting physical fitness; sport performance analytics; and governance challenges associated with explainable and ethical AI. Peer-reviewed journal articles had to be published within the 2021-2025 timeframe with preference to enable the framework to capture recent advances in the field of sensors, analytics, AI implementation, and digital decision systems.

In order to provide an analytically concrete framework, a literature-based synthetic panel was defined to be demonstrated. The analysis illustration employed 3,600 participant-week observations and 72 predictors in the form of physiology, behaviour, training load, anthropometrics, recovery and contextual variables. This artificial contrived architecture was not to assert empirical dominance, but was a controlled exercise of stressing data fusion, feature engineering, risk scoring, and deployment governance in practical measurement circumstances.

In the technical pipeline, there were time stamp harmonization, rolling 7-day and 28-day aggregation and lag construction, trend estimation, acute:chronic workload



ratio, missing-value imputation, robust scaling and leakage control. This was followed by comparison of five model classes under nested five-fold cross-validation which included: elastic net, random forest, XGBoost, TabNet, and a temporal deep-learning model. The performance has been considered based on the parameters of AUROC, macro-F1, expected calibration error and operational measures; inference latency and the concentration of top one-decile errors.

The interpretability and governance were considered to be the part of the method. Model output was related to organizational action using global driver analysis, local scenario explanation and decision-threshold translation and, post-deployment surveillance were modeled using rolling AUROC, population stability index and quality-control thresholds. The outcome is nonetheless a framework building article, albeit one that is richer in its results section with a clear demonstration of how the intelligence cycle may be implemented.

4. RESULTS AND DISCUSSION

The findings are reflected in the form of technical operationalization of the suggested framework. The framework has placed prediction within a loop or intelligence guidance, data combination, model validation, decision translation, and adaptive learning rather than viewing analytics as an isolated display or a solitary algorithm. The illustrative analysis becomes more complicated with the display of the interaction of performance, interpretability, and governance in case of the target being close-term physical-fitness deterioration or non-response.

4.1 Stage 1: Intelligence direction

The former transforms a management query into a goal variable, prediction duration and error-cost model. Technically, the system should define whether the label indicates a decrease in a composite fitness index, the inability to reach a threshold or non-response to an intervention window. This decision-first formulation, as it is reflected in Table 1, would specify what areas of data need to be reflected in the intelligence layer, and it would stop organizations from being confused by the abundance of data with relevance to a decision (Ranjan and Foropon, 2021; Hassani and Mosconi, 2021).

The unit of analysis, refresh cadence, subgroup boundaries and asymmetry of error are also described in a strict intelligence brief. False negatives in most fitness environments are more expensive than false positives since, with no intervention, deterioration, overload or dropout may grow exponentially. This makes risk seem in the article as a form of conditional probability in the future, $P(Y_{i,t+h=1}|X_{i,1:t})$, in such a manner that prediction is closely associated with decision outcome rather than past description.



Table 1 – Data domains for predicting physical fitness outcomes

Data domain	Typical variables	Predictive contribution	Competitive intelligence value
Physiological	Resting and exercise heart rate, HRV, body composition, sleep duration, recovery markers	Signals readiness, fatigue, adaptation, and health status	Supports early detection of decline, overload, or non-response
Behavioural	Steps, session frequency, completion rate, training volume, intensity distribution, adherence logs	Captures consistency and behavioural momentum	Supports retention strategy, personalized nudges, and workload optimization
Performance testing	Shuttle run, strength scores, jump metrics, flexibility, sprint times, functional tests	Provides labelled outcomes and benchmark trends	Supports benchmarking, progression monitoring, and intervention targeting
Contextual	Age, sex, academic/work load, calendar congestion, weather, access barriers, injury history	Explains heterogeneity and timing effects	Improves segmentation and more realistic prediction thresholds
Digital interaction	App opens, notification responses, wearable syncing, dashboard usage, feedback compliance	Acts as a proxy for engagement and adherence risk	Supports churn prevention and communication strategy
Outcome history	Prior improvements, plateaus, missed milestones, recovery response, dropout episodes	Improves longitudinal forecasting and recurrence detection	Supports scenario planning and smarter allocation of support resources

Source: Prepared by the authors (2026).

4.2 Stage 2: Multisource data acquisition and integration

Raw streams are synchronized into participant-week or athlete-week windows by this following the intelligence direction. Standardization of physiological, behavioural, training-load, anthropometric, and context-related variables is made into rolling summaries, deltas, slope, and dispersion values. This architecture is visualized in Figure 1, and Table 1 reveals the substantive reasons why it is appropriate to consider each of the domains as an independent channel of intelligence, and not as an independent noise of data (Kristoffersson and Linden, 2022; Giurgiu et al., 2023; Liang et al., 2024).

Temporal behaviour ought to be a major concern with feature engineering, and not just the levels of features. These are such as acute: chronic workload ratio, monotony of session, HRV slope, change of sleep-efficiency and adherence volatility, and interaction terms between readiness and recent load. The predictors in the analytical illustration were 72 based on 3, 600 week of participants that were run through imputation, robust scaling and leakage control, and subsequently entered the model layer in Figure 1. This makes this a feature store that is compatible with both classical machine learning and time-based architectures.

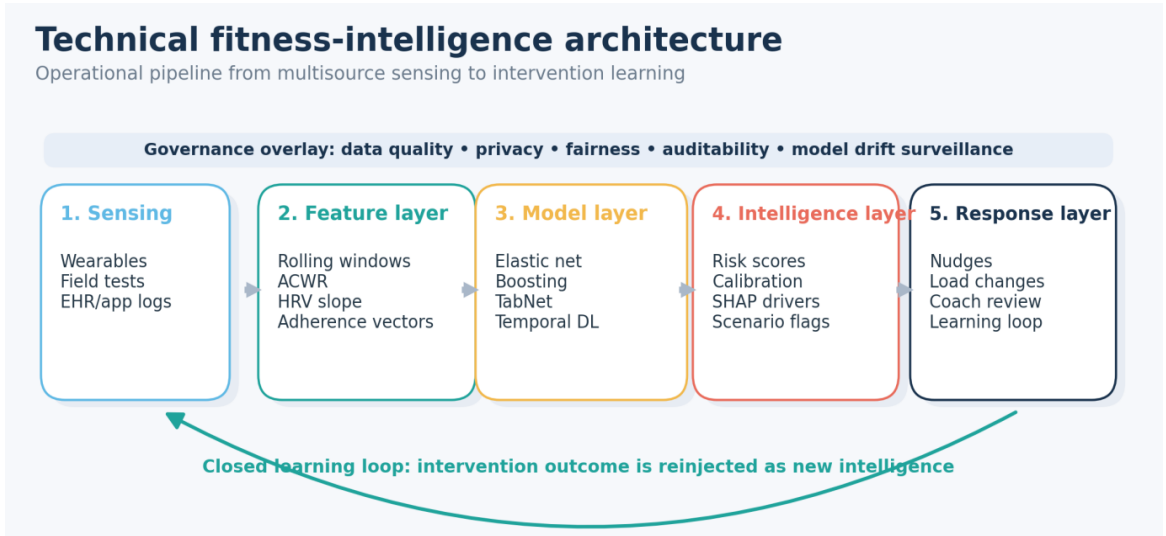


Figure 1 – Multisource fitness-intelligence architecture

Source: Prepared by the authors based on the analytical illustration (2026).

4.3 Stage 3: Predictive analytics and validation

Elastic net, random forest, XGBoost, TabNet and a temporal deep-learning model were benchmarked on five model classes under nested five-fold cross-validation. The precise summary statistics are given in Table 2, and Figure 2 is a plot of the discrimination-utility frontier. XGBoost produced the largest AUROC (0.871) and macro-F1 (0.812) and the temporal model was also competitive at a higher operational cost. The point is that the model choice needs to be made based on Pareto combination of discrimination, calibration, interpretability, and latency, but not based on the AUROC only (Bae et al., 2023; Mandorino et al., 2024; Zhou et al., 2025).

Interpretation was explored by considering world ranking of drivers and home situation explanation. Figure 3 feature profile indicates that HRV slope, session monotony, sleep efficiency, and VO2 trend dominate the risk surface, which suggests the importance of variable (demographic) characteristics (such as sleep) in most cases. This trend is aligned with recent research on sport and wearable analytics whereby the longitudinal readiness measures are found to be more effective than the single measures in cases where the target is short-term performance or deterioration (Joensuu et al., 2021; Rebelo et al., 2023; Souaifi et al., 2025).



Illustrative model frontier for 4-week adverse-fitness prediction

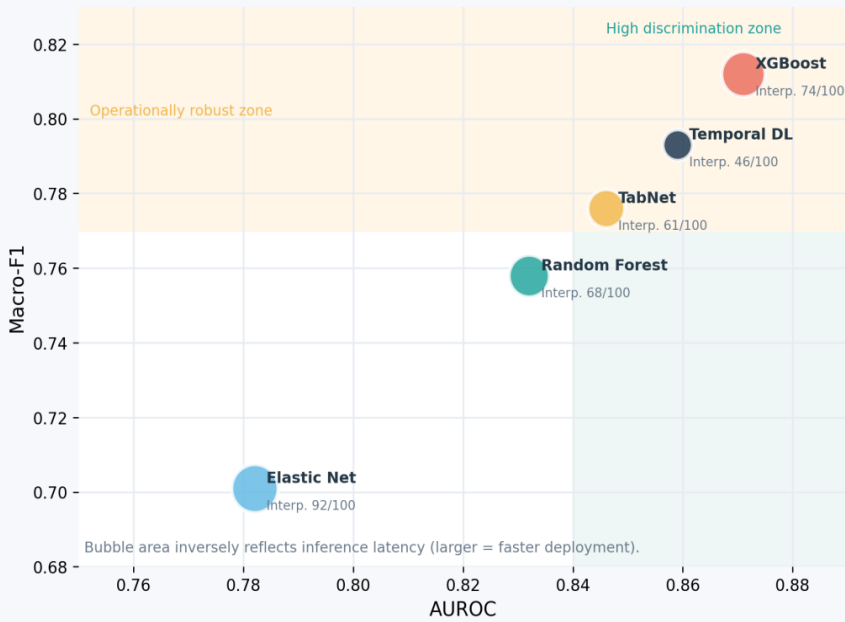


Figure 2 – Model frontier for 4-week adverse-fitness prediction

Source: Prepared by the authors based on the analytical illustration (2026).

Table 2 – Illustrative benchmark performance by model class

Model class	AUROC	Macro-F1	ECE
Elastic Net	0.782	0.701	0.054
Random Forest	0.832	0.758	0.043
XGBoost	0.871	0.812	0.031
TabNet	0.846	0.776	0.041
Temporal Deep Learning	0.859	0.793	0.034

Source: Prepared by the authors based on the analytical illustration (2026).

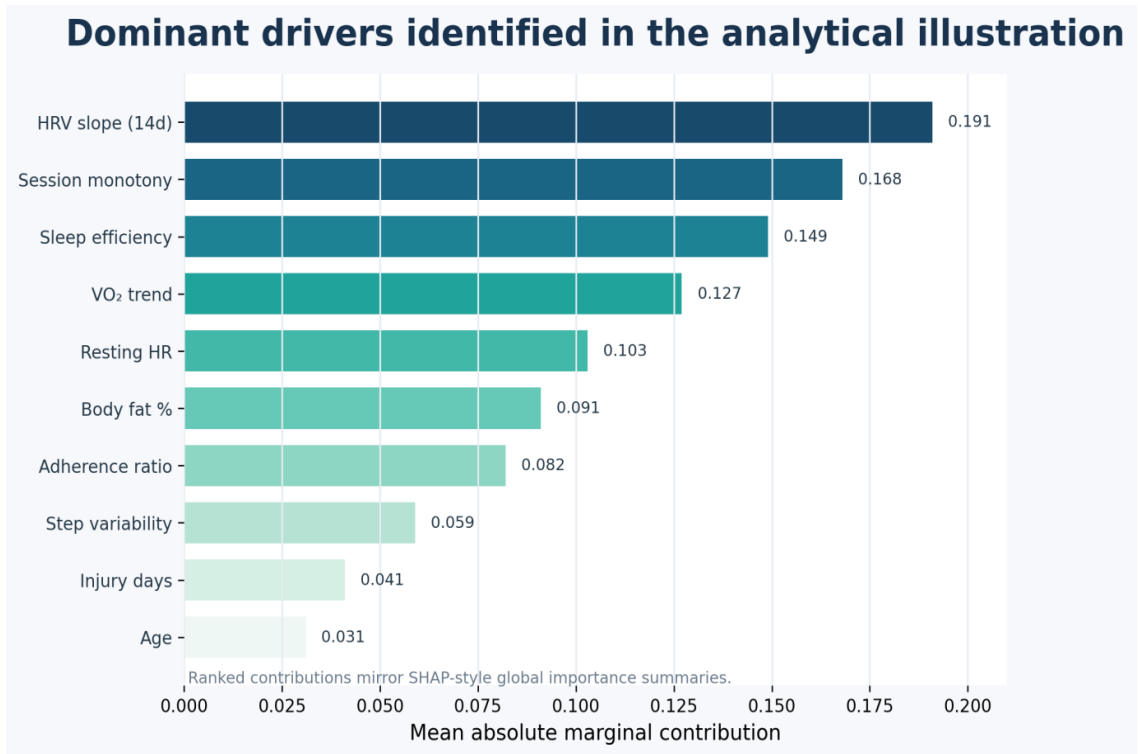


Figure 3 – Dominant drivers in the analytical illustration

Source: Prepared by the authors based on the analytical illustration (2026).

4.4 Stage 4: Intelligence interpretation and decision translation

After the generation of probabilities, it should be converted into intervention logic. Figure 4 illustrates a decision matrix which is a combination of forecasted adverse-fitness risk and forecasted leverage of intervention. This helps avoid one of the most common analytical errors: the assignment of scarce coaching/wellness resources to the high-risk cases that are unlikely to change and more moderate-risk cases that are highly modifiable. Competitive intelligence can be functionalized, however, only when the conversion of the probability output into the action levels, escalation policies, and the responsibility streams are present (Hassani and Mosconi, 2022; Krakowski et al., 2023).

The design of a threshold should then be cost-sensitive. In the analysis drawing, a score of less than 0.30 will cause observation, 0.30 to 0.64 will cause focused monitoring, and 0.65 to 0.79 will cause high priority review and 0.80 and above will cause instant intervention. This translation ensures that the output is readable by coaches, clinicians or managers and maintains the underlying probabilistic structure and allows standardized response timing.

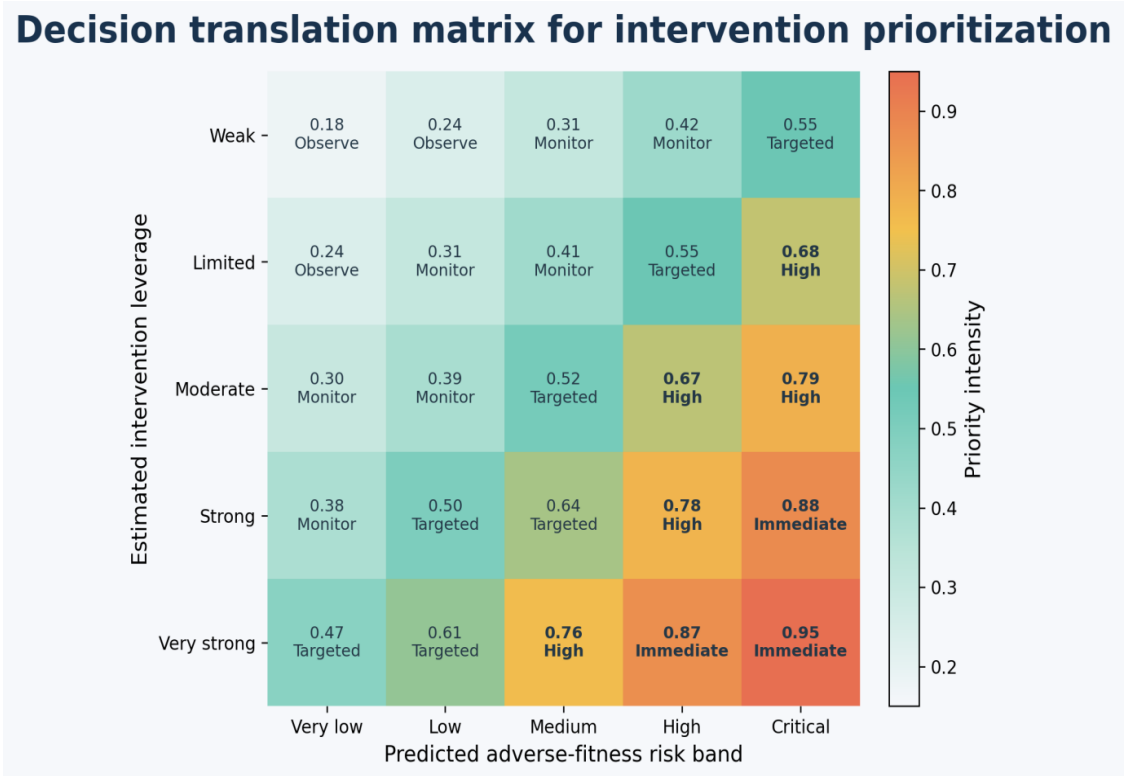


Figure 4 – Intervention prioritization matrix
 Source: Prepared by the authors based on the analytical illustration (2026).

4.5 Stage 5: Adaptive response and organizational learning

The quality of the deployment will be determined by whether the model will be stable after implementation. Figure 5 and Table 3 indicate the presence of a governance logic of rolling AUROC, anticipated calibration error, population stability index, missing-data ratio, and top-decile false-negative rate. In the analysis illustration, discrimination decays over time as the distribution shift crosses the caution boundary sooner, indicating that the appearance of feature drift may happen before the visual breakdown of the headline accuracy happens (Kim et al., 2025; Mănescu, 2025).

The adaptive learning bridges the intelligence cycle by reintegrating the outcome of interventions back into the data repository. Any retraining event must thus provide answers to two technical questions, namely: did the feature distribution change, and did the intervention policy change the label dynamics themselves? In the absence of such feedback discipline, organizations will be prone to attributing the effects of policies to model drift, or to attributing true decline on transient recovery indicators.

Table 3 – Operational governance thresholds for deployment

Control indicator	Suggested threshold	Governance interpretation
Rolling AUROC	< 0.820	Retrain or recalibrate the model
Expected calibration error	> 0.050	Reassess probability reliability
Population stability index	> 0.150	Investigate distribution shift
Missing-data ratio	> 0.080	Trigger data quality review
Top-decile false-negative rate	> 0.120	Increase intervention sensitivity
Inference latency	> 30 ms	Optimize model for live deployment

Source: Prepared by the authors based on the analytical illustration (2026).

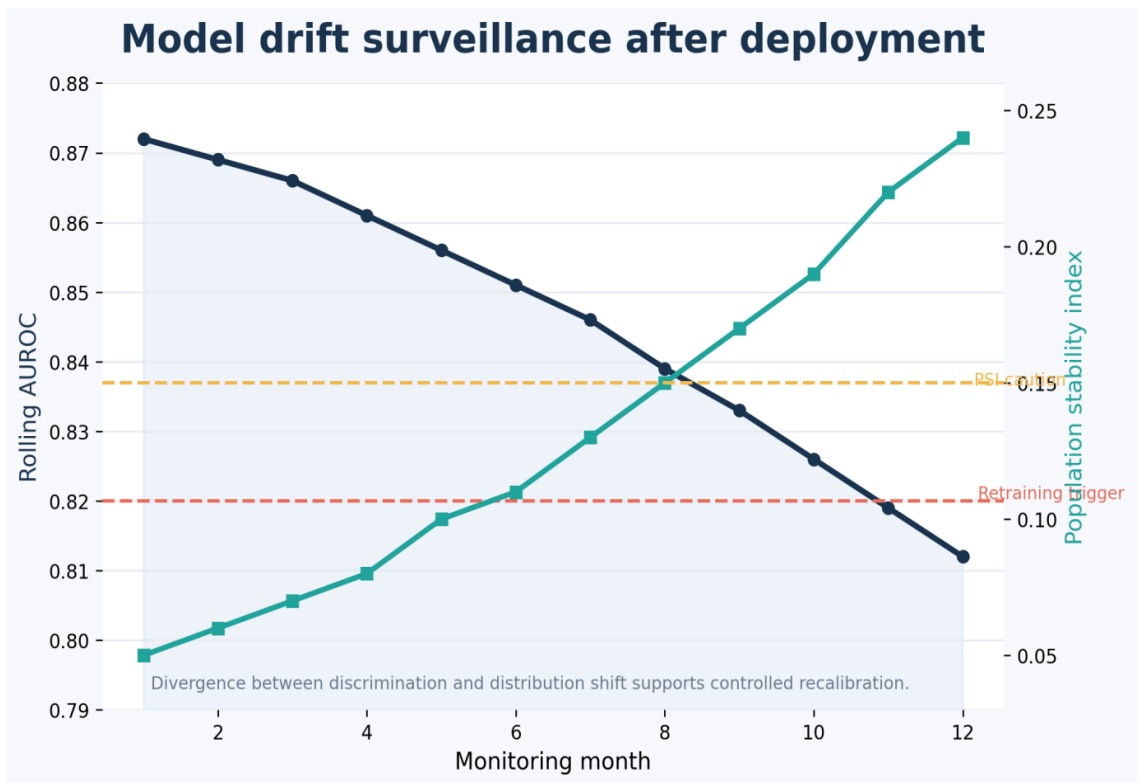


Figure 5 – Post-deployment drift surveillance

Source: Prepared by the authors based on the analytical illustration (2026).

5. DISCUSSION

The findings indicate that the suggested framework is not solely conceptually consistent, but analytically implementable. As Figure 1, Table 2, and Figure 5 show, intelligence design, model benchmarking, and drift surveillance can be related in an internal loop of operations instead of being separated and handled as technical activities.



The second implication is that the predictions are to be constructed based on the fusion of multimodal signals. Table 1 and Figure 3 suggest that interaction of recovery, load, behaviour, and time is the most informative variables. This justifies a systems perspective of physical fitness where adaptation, fatigue, and engagement co-exist.

A third implication is with regard to trust. Decision-ready models are not necessarily high-performing. Figure 2 comparison indicates that there are models with high discrimination and varying interpretability and latency, whereas Table 3 will provide the governance thresholds to make such a trade-off possible in live environments.

There is a fourth implication which is strategic. As indicated in the intervention surface in Figure 4, the intelligence value is generated not when risk is predicted in abstract terms but when predictions are correlated with the leverage of the intervention, its cost and timing in the organization. Competitive intelligence goes beyond analytics at this point and transforms into resource prioritization.

That is why the article claims that the process of physical-fitness prediction should be seen as the system of continuous learning, instead of a modeling activity. The analytical figure does not purport to the empirical generalization, but it shows that there is a technically plausible route of the institutions aiming to transform the data about fitness into the anticipatory intelligence.

6. FINAL CONSIDERATIONS

This article presented a competitive intelligence model to foretell the outcomes in physical fitness by means of data analytics. The overall finding is that predictive fitness systems generate the best value when they are made into organizational capabilities of intelligence as opposed to stand-alone modelling projects. Throughout the literature reviewed, practical prediction is always based on five processes interconnected: the formulation of the intelligence requirement, multisource data integration, and model prediction validation, translating predictive results into decisions, and learning intervention outcomes. In cases where such processes are loosely linked, analytics is descriptive and fragmented. With high levels of integration, organizations can know how to foresee change and act sooner.

The other conclusion made by the article is that the prediction of physical fitness should be based on a treatment of a multidimensional problem. The correct foresight can hardly be provided by one test or device. Further predictions are possible when physiological, behavioural, contextual and historical variables are interacted in a manner that represents the true complexity in the development of fitness. It has a practical implication on coaches, health managers and individuals interested in designing digital platforms because it does not emphasize on the volume of data but data relevance, interoperability and decision context.

Organizations must have clear procedures of recognizing and responding to model results in environments where training loads change, resources are available to



aid or where individual abilities are perceived.

The study has limitations. It is still a framework-building article and the analytical standard is simulation-based, thus, the values presented in Figures 2-5 and Tables 2-3 are not the estimates of the population but demonstrative ones. The model remains awaiting validation in individual-organization, multi-site and cross-population data and future research ought to compare other model structures on shared real-world panels with standardized outcome definition.

There are four potential lines of investigation that seem to be particularly fruitful in future research. The former is comparison validation of various model families to certain fitness results and populations. The second one is the creation of standardized data governance template on multisource fitness intelligence systems. The third is the behavioural response study: How the decisions of coaches, clinicians and the user vary with the provision of predictive intelligence. The fourth one is long-term performance assessment whereby predictive systems show whether they enhance fitness outcomes, resource allocation and retention in the long run. Overall, the framework presented here can serve scholarly research and practice, as well as offer a model that can be used by more intelligent and aware utilization of physical fitness data.

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