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Research Article

Intelligent Clinical Decision Support Based on the Data Envelopment Analysis of Fitness Data

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Abstract

We consider a case study of intelligent clinical decision support based on the Data Envelopment Analysis of fitness data. Fitness data is collected from a smart sports band. Data Envelopment Analysis is conducted on the fitness data to assess fitness level and compare with peer health data. Artificial Intelligence AI is used to process data envelopment analysis outcomes. Clinical decision is taken based on the AI enhanced analysis. This case study has the potential to improve primary care practice with the support of clinical decision, Data Envelopment Analysis, smart sports bands technology, and Artificial Intelligence.

Keywords: Artificial intelligence, Data envelopment analysis, Fitness, Decision support, Clinical medicine, Case study

Introduction

Clinical Decision Support (CDS) technologies in primary care have evolved from early rule-based expert systems that offered static diagnostic, to electronic health record EHR-integrated tools providing medication alerts and preventive care reminders, and now to Artificial Intelligence AI-driven platforms that leverage machine learning, predictive analytics, and wearable data for personalized recommendations. This trajectory reflects a shift from rigid knowledge bases toward adaptive, real-time systems that enhance patient safety, reduce clinician workload, and support population health management. Clinical Decision Support (CDS) technologies enable ambient intelligence, interoperability, and compliance with regulation frameworks. This paper presents a review of the structure of fitness data from smart watches (sports bands) mobile applications (app) and a review of the use of Data Envelopment Analysis on fitness data. Following these reviews, we consider a case study that combines data envelopment analysis and artificial intelligence to enhance clinical decision support based on fitness data. The paper concludes with the potential and limitations of combining Data Envelopment Analysis and artificial intelligence AI to enhance clinical decision support based on fitness data and the future work needed [8,22].

Fitness Data

Fitness bands such as Fitbit, Garmin, Apple Watch, and Xiaomi Mi Band generate structured datasets that include user profile information, activity tracking, heart rate monitoring, sleep stages, exercise sessions, calorie expenditure, and environmental sensor readings. These data are typically exported in formats such as JSON (JavaScript Object Notation), CSV (Comma-Separated Values), or proprietary files, allowing integration into analytics platforms and clinical decision support systems [4]. The structure ensures time-series consistency, sensor calibration, and interoperability with healthcare standards like FHIR (Fast Healthcare Interoperability Resources), particularly in Apple's HealthKit ecosystem. Structured fitness data are increasingly used in preventive healthcare and fitness analytics, enabling personalized monitoring and predictive modeling [1,18]. A comparative analysis reveals that Apple Watch and Garmin lead in sensor richness and clinical-grade metrics, with Apple offering ECG (Electrocardiogram) and HIPAA (HEALTH INSURANCE PORTABILITY AND ACCOUNTABILITY ACT)-compliant HealthKit integration, while Garmin emphasizes advanced GPS (Global Positioning System) and VO_2 max (Volume Oxygen Maximum) tracking. Fitbit balances wellness and stress monitoring through EDA (Exploratory Data Analysis) sensors, whereas Xiaomi provides consumer-level tracking with limited clinical reliability. Export formats also differ. Apple HealthKit aligns with FHIR (Fast Healthcare Interoperability Resources) standards, Garmin uses FIT files (Flexible and Interoperable Data Transfer) optimized for sports analytics, Fitbit relies on OAuth-based APIs (Application Interfaces), and Xiaomi supports CSV/JSON via its Mi Fit app. These structural differences influence the applicability of fitness data in clinical pipelines, sports performance analytics, and consumer wellness platforms, with integration challenges ranging from proprietary formats to ecosystem lock-in [2,9,10,23,24] (Table 1).

Table 1: Comparative Matrix: Fitness Band Data Structures.

Device	Sensors	Data Types	Export Format	Integration
Fitbit	7 sensors (PPG HR, SpO_2, accelerometer, gyroscope, EDA for stress)	Steps, HR, HRV, sleep stages, calories, stress	JSON, CSV via Fitbit Web API	Cloud API, OAuth 2.0, limited FHIR alignment
Garmin	10 sensors (PPG HR, SpO_2, GPS multi-band, barometer, gyroscope, ECG)	HR, HRV, VO_2 max, GPS routes, elevation, exercise sessions	Proprietary FIT files, CSV, JSON	Garmin Connect API, strong GPS + sports metrics
Apple Watch	10–11 sensors (PPG HR, SpO_2, ECG, GPS, gyroscope, altimeter, temp)	HR, HRV, ECG, fall detection, sleep, activity rings	Apple HealthKit (FHIR-aligned), JSON	Deep iOS integration, HIPAA-compliant pipelines
Xiaomi Mi Band	5–6 sensors (PPG HR, SpO_2, accelerometer, gyroscope, temp)	Steps, HR, sleep, calories, basic workouts	CSV, JSON via Mi Fit app	Limited API, mostly consumer-level exports

The core structure of fitness band data include:

1. User Profile

a. Age, gender, height, weight, baseline health metrics.

b. Used for calibration of calorie burn and VO_2 max estimates.

2. Activity Tracking

a. Steps, distance, floors climbed, active minutes.

b. Often stored as time-series data with timestamps.

3. Heart Rate

a. Resting heart rate, max heart rate, HR variability.

b. Continuous monitoring with 1–5 second intervals.

4. Sleep Data

a. Sleep stages (light, deep, REM), duration, interruptions.

b. Structured as nightly logs with stage transitions.

5. Exercise Sessions

a. Type of workout (running, cycling, swimming).

b. Metrics: pace, cadence, elevation, GPS route.

6. Calories & Energy

a. Active calories vs. basal metabolic rate.

b. Linked to activity and heart rate data.

7. Environmental Sensors

a. GPS coordinates, altitude, temperature, sometimes SpO_2.

b. Stored as geospatial + physiological datasets.

8. Export Formats

a. Commonly JSON, CSV, or proprietary app databases.

b. Structured with timestamps, sensor IDs, and units (Figure 1).


```json
{
  "user": {"age": 28, "weight": 70, "height": 175},
  "activity": [
    {"timestamp": "2026-08-08T22:45:00", "steps": 120, "distance_m": 95}
  ],
  "heart_rate": [
    {"timestamp": "2026-08-08T22:45:00", "bpm": 78}
  ],
  "sleep": {
    "date": "2026-08-07",
    "stages": [
      {"stage": "light", "duration_min": 120},
      {"stage": "deep", "duration_min": 90}
    ]
  },
  "exercise": {
    "type": "running",
    "duration_min": 45,
    "avg_pace": "5:30/km",
    "route": "GPS_coordinates"
  }
}
```


Figure 1: Example Fitness Data in JSON Format.

Structured fitness data allows integration into fitness analytics, preventive healthcare, and clinical decision support systems.

Data Envelopment Analysis of Fitness Data

Data Envelopment Analysis (DEA) is a non-parametric method in operations research and economics that evaluates the relative efficiency of comparable entities, known as Decision-Making Units (DMUs), by analyzing the ratio of multiple inputs to multiple outputs without assuming a specific production function. DEA constructs an efficiency frontier based on the most efficient DMUs and measures the performance of others against this benchmark, making it useful in sectors such as healthcare, banking, education, and logistics. It can be input-oriented, focusing on minimizing inputs for given outputs, or output-oriented, aiming to maximize outputs for given inputs, with models such as CCR and BCC accounting for constant or variable returns to scale. The strength of DEA lies in its ability to handle multidimensional datasets and provide benchmarking insights, though it is sensitive to data accuracy and requires careful interpretation of efficiency scores [1,5,18,23] (Table 2).

Table 2: Comparative Table of DEA Models.

Model	Orientation	Returns to Scale	Key Features	Applications
CCR Model	Input- or Output-oriented	Constant returns to scale	First DEA model; efficiency frontier based on proportional scaling	Banking, healthcare, logistics
BCC Model	Input- or Output-oriented	Variable returns to scale	Accounts for scale inefficiency; separates pure technical efficiency	Hospitals, education, public services
Additive Model	Non-radial	Variable returns to scale	Considers input/output slacks directly; measures inefficiency	Resource allocation, performance benchmarking
Slacks-Based Measure (SBM)	Non-radial	Variable returns to scale	Focuses on slack variables; robust efficiency measurement	Environmental efficiency, sustainability
Network DEA	Input- or Output-oriented	Flexible	Evaluates multi-stage processes and internal structures	Supply chains, production systems

Dea Models

Data Envelopment Analysis (DEA) models are mathematical formulations that assess efficiency by comparing multiple inputs and outputs across decision-making units (DMUs), with the most common being the CCR (Charnes, Cooper and Rhodes) model *Charnes, Cooper, & Rhodes, et al.,* (1978), which assumes constant returns to scale, and the BCC (Banker, Charnes, & Cooper) model *Banker, Charnes, & Cooper, et al.,* (1984), which accounts for variable returns to scale. These models can be input-oriented, minimizing resources for a given level of output, or output-oriented, maximizing outputs with fixed inputs, thereby providing flexibility depending on the evaluation context. Extensions such as the Additive Model, Slacks-Based Measure (SBM), and Network DEA further refine efficiency measurement by addressing slack variables, non-radial efficiency, and multi-stage processes [20]. DEA models are widely applied in healthcare, education, banking, and logistics, offering benchmarking insights and identifying best-practice units, though they remain sensitive to data quality and require careful interpretation of efficiency scores [3,5,6].

Dea CRS Model

The Constant Returns to Scale (CRS) model in Data Envelopment Analysis (DEA), also known as the CCR model after [5], assumes that efficiency can be measured under the condition that proportional increases in inputs lead to proportional increases in outputs. This model constructs an efficiency frontier by identifying the most efficient Decision-Making Units (DMUs) and then evaluates all others relative to this frontier. The CRS assumption implies that scale does not affect efficiency, meaning that doubling inputs should ideally double outputs. The CCR model can be applied in both input-oriented and output-oriented forms, depending on whether the focus is on minimizing resource use or maximizing output production. While it provides a foundational benchmark for efficiency analysis, its limitation lies in not accounting for scale inefficiencies, which later led to the development of the BCC model that incorporates variable returns to scale [3,5,6].

DEA Applied to Fitness Data

Applying Data Envelopment Analysis (DEA) to fitness data involves benchmarking the efficiency of individuals or devices (decision-making units, DMUs) by comparing multiple inputs, such as time spent exercising, calories consumed, or physiological effort, against outputs like steps taken, distance covered, heart rate improvement, or VO_2 max (volume of oxygen) gains. By constructing an efficiency frontier, DEA can identify which athletes or fitness trackers operate most efficiently and highlight areas of inefficiency for others. For example, sports bands like Fitbit or Apple Watch generate multidimensional datasets (steps, heart rate, sleep, calories), which can be modeled in DEA to evaluate how effectively users convert physical effort into measurable health outcomes [21]. This approach is particularly valuable in preventive healthcare and personalized training, as it allows practitioners to distinguish between scale inefficiency (e.g., underutilization of training time) and pure technical inefficiency (e.g., poor conversion of effort into fitness gains), thereby supporting evidence-based decision-making in clinical and sports contexts [3,5,6,23].

Case Study

Fitness Data

Table 3: Fitness Data collected.

Metric	Sample Value
Steps	10,245
Heart Rate (avg bpm)	78
Calories Burned	520 kcal
Sleep Duration	7h 15m
VO_2 Max	46 ml/kg/min
GPS Distance	5.2 km
ECG Recording	Normal sinus rhythm

Fitness data are collected from ALCATEL sports band. These include various health data indicators as shown in Table 3 [19] (Table 3).

Application of CRS Dea Model

Applying the Constant Returns to Scale (CRS) DEA model, also known as the CCR model, to fitness band data involved evaluating how efficiently individuals convert multiple inputs (e.g., exercise time, calories consumed, average heart rate) into outputs (e.g., steps taken, distance covered, VO_2 max, sleep quality). Under the CRS assumption, proportional increases in inputs should yield proportional increases in outputs, meaning that doubling exercise time and calorie expenditure should ideally double fitness outcomes. Using the sample fitness data, calorie burn can be treated as DMUs. DEA helps in constructing an efficiency frontier from the most efficient unit and compares others against it, identifying scale inefficiencies and benchmarking performance. This application allows healthcare providers and trainers to assess which users achieve optimal health outcomes relative to their effort, thereby supporting preventive healthcare and personalized fitness strategies [3,5,6,23]. The Constant Returns to Scale (CRS) DEA model, also known as the CCR model, when applied to fitness data from sports bands, evaluates how efficiently individuals convert proportional inputs into proportional outputs. For example, inputs such as exercise time, calories consumed, and average heart rate can be compared against outputs like steps taken, distance covered, VO_2 max, or sleep quality. Under CRS assumptions, doubling exercise time and calorie expenditure should ideally double the fitness outcomes, meaning efficiency is scale-independent. By constructing an efficiency frontier, DEA benchmarks identify optimal health outcomes relative to effort. This application supports preventive healthcare and clinical decision support by distinguishing between efficient and inefficient use of fitness resources, thereby guiding personalized training and healthcare strategies [3,5,6,23].

Using Excel Dea Solver

Constant Returns to Scale (CRS) DEA model was applied to fitness data in Excel Solver. We considered sports band outputs such as steps, distance, VO_2 max, and sleep duration, with inputs like exercise time, calories consumed, and average heart rate. In Excel, each Decision-Making Unit (DMU) is represented as a row, with Solver used to maximize the efficiency score (θ) subject to linear constraints that ensure proportional scaling of inputs and outputs. Under CRS assumptions, doubling inputs should proportionally double outputs, so Solver identifies the efficiency frontier by assigning optimal weights to inputs and outputs. The most efficient DMUs receive a score of 1, while others fall below, highlighting inefficiencies in converting effort into fitness outcomes. This approach allows benchmarking across users, supporting preventive healthcare and clinical decision support [3,5,6,23] (Table 4).

Table 4: Excel Solver Used to apply DEA to Fitness Data (DMU).

Exercise Time (min)	Calories Consumed	Avg Heart Rate (bpm)	Steps	Distance (km)	VO_2 Max	Sleep Duration (hrs)
60	2200	78	10,245	6.1	42	7.2
75	2500	82	11,500	8.0	46	6.8
70	2400	80	10,800	7.2	44	7.0
55	2100	76	9,200	5.5	40	6.5

The Solver objective is to maximize the efficiency score (θ) for each DMU by assigning optimal weights to inputs and outputs, subject to CRS constraints that ensure proportional scaling. Efficient DMUs will score 1, while less efficient ones will score below 1, allowing benchmarking across users [3,5,6,23].

Solver Setup (CRS DEA – Input-Oriented Example)

a. Objective Cell: Maximize θ (efficiency score).

b. Variable Cells: Input and output weights.

c. Constraints: Weighted outputs ≤ weighted inputs for all DMUs.

d. Efficiency score θ ≤ 1.

e. Non-negativity for all weights.

f. Excel Solver calculates θ for each DMU.

Combining AI Decision Support

Combining Artificial Intelligence (AI) with Data Envelopment Analysis (DEA) in fitness data analytics enables more robust benchmarking and predictive modeling by integrating multidimensional sensor data from sports bands with efficiency frontier analysis. DEA provides a mathematical framework to evaluate how effectively inputs such as exercise time, calories consumed, and average heart rate are converted into outputs like steps, VO_2 max, and sleep quality, while AI enhances this process by detecting nonlinear patterns, handling large-scale time-series data, and generating personalized recommendations. For example, AI-driven clustering can group users with similar fitness profiles, and DEA can then benchmark their efficiency relative to the best performers, supporting preventive healthcare and clinical decision support. This hybrid approach leverages DEA's interpretability with AI's predictive power, offering a comprehensive tool for optimizing fitness outcomes and guiding individualized interventions [1,3,5,6].

Enhancing Clinical Decision Support (CDS) can be obtained by combining Artificial Intelligence (AI) with Data Envelopment Analysis (DEA) applied to fitness data. This allows healthcare providers to move beyond descriptive monitoring toward predictive and prescriptive analytics. DEA establishes efficiency frontiers by benchmarking how effectively individuals or devices convert inputs such as exercise time, calories consumed, and heart rate into outputs like steps, VO_2 max, and sleep quality, while AI augments this by detecting nonlinear patterns, integrating large-scale time-series data, and generating personalized recommendations. Together, DEA provides interpretability and benchmarking, while AI supplies adaptive learning and predictive modeling, enabling CDS (Clinical Decision Support) systems to identify at-risk patients, optimize preventive interventions, and tailor fitness or rehabilitation programs. This hybrid approach strengthens evidence-based decision-making by combining DEA's transparency with AI's computational power, ultimately improving patient outcomes and resource allocation in preventive healthcare [1,3,5,6]. AI tools that can be integrated with DEA for fitness data include machine learning frameworks (TensorFlow Lite, PyTorch, Core ML), computer vision libraries (MediaPipe, Sportsbox AI), conversational AI (OpenAI GPT family), and wearable software development kits SDKs (Fitbit API, Apple HealthKit). These tools enhance DEA benchmarking by enabling pose estimation, predictive analytics, and personalized coaching, making efficiency analysis of fitness data more actionable in clinical and sports contexts [7,11-17] (Table 5).

Table 5: AI Tools Used in combination with Fitness Data and DEA.

AI Tool	Core Function	DEA Integration	Use Case
TensorFlow Lite	On-device ML inference	Handles large-scale time-series fitness data for DEA inputs/ outputs	Heart rate & calorie prediction
PyTorch & TorchServe	Deep learning framework	Builds predictive models to complement DEA efficiency scores	VO_2 max forecasting
MediaPipe (Google)	Real-time pose estimation	Provides biomechanical input variables for DEA	Rep counting, form analysis
Sportsbox AI	3D biomechanics analysis	Supplies motion-capture outputs for DEA benchmarking	Golf swing efficiency
OpenAI GPT	Conversational coaching	Generates personalized recommendations based on DEA results	Adaptive workout plans
Apple HealthKit SDK	Wearable integration	Provides structured health metrics for DEA	ECG, sleep, steps
Fitbit API	Sensor data export	Supplies multidimensional fitness inputs for DEA	Steps, calories, sleep

Enhanced Clinical Decision Support

Enhanced Clinical Decision Support (CDS) emerges when Artificial Intelligence (AI) is combined with Data Envelopment Analysis (DEA) applied to fitness data, as this hybrid approach leverages DEA's benchmarking transparency with AI's predictive and adaptive capabilities. DEA evaluates efficiency by comparing how inputs such as exercise time, calories consumed, and heart rate are transformed into outputs like steps, VO_2 max, and sleep quality, while AI augments this process by analyzing large-scale time-series data, detecting nonlinear relationships, and generating personalized recommendations. Together, they enable CDS systems to identify inefficiencies in patient fitness behaviors, predict health risks, and tailor preventive interventions or rehabilitation programs. This integration strengthens evidence-based decision-making, improves patient outcomes, and optimizes healthcare resource allocation by combining DEA's interpretability with AI's computational power [1,3,5,6].

Conclusion

The integration of Artificial Intelligence (AI) with Data Envelopment Analysis (DEA) in fitness data analytics presents both limitations and promising avenues for future work. Current limitations include DEA's sensitivity to noisy or incomplete sensor data, the assumption of proportional scaling in CRS models that may not reflect real-world physiological responses, and challenges in integrating heterogeneous datasets from different sports bands. Additionally, AI models, while powerful, can reduce interpretability compared to DEA's transparent benchmarking, raising concerns for clinical decision support. Future work should focus on developing hybrid DEA–AI frameworks that combine DEA's efficiency frontier with AI's predictive modeling, incorporating advanced techniques such as deep learning for time-series fitness data, federated learning to preserve privacy, and explainable AI to maintain clinical trust. Expanding applications into preventive healthcare, rehabilitation monitoring, and personalized training programs will strengthen evidence-based decision-making, while cross-device standardization of fitness metrics will enhance comparability and robustness [1,3,6].

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Conflict of Interest Statement

There is no conflict of interest.

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