



Research Article

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Building a Library of AI Prompts for Clinical Decision Support Based on Dea of Fitness Data

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To Cite This article: Ibrahim H Osman, Soha Maad* and Baydaa Al Ayoubi, Building a Library of AI Prompts for Clinical Decision Support Based on Dea of Fitness Data. *Am J Biomed Sci & Res.* 2026 32(4) AJBSR.MS.ID.004188, DOI: [10.34297/AJBSR.2026.32.004188](https://doi.org/10.34297/AJBSR.2026.32.004188)

Received: 📅 October 11, 2026 Published: 📅 October 23, 2026

Abstract

We develop an approach to manage Artificial Intelligence AI prompts and AI autonomous agents for clinical decision support based on Data Envelopment Analysis (DEA) of fitness data. We implement an integration framework for AI and DEA developed in (Osman, et al., 2026) [4]. The integration framework is based on mix and match of AI and DEA models and tools and format and structure of input and output of DEA and AI. The framework is applied on fitness data from sports band. DEA CRS (Constant Return to Scale) and VRS (Variable Return to scale) input and output oriented models. DEA excel solver is used to analyse the data and use AI for enhanced clinical decision support based on fitness analytics. An approach to manage AI prompts that help in clinical decision is proposed to prescribe various fitness programs to patients based on their fitness data. The paper concludes with future work to enhance and populate the AI library of prompts for clinical decision support based on fitness data.

Keywords: Artificial intelligence, Data envelopment analysis, Fitness, Decision support, Clinical medicine, Integration, Data structure, AI prompts, Library, Management

Introduction

We developed in (Osman, et al., 2026a) [4] a framework for the integration of Data Envelopment Analysis and Artificial Intelligence based on mix and match of models and tools and input and output data structure. The framework offers three integration models based on sequence of input and output of DEA and AI. We use in this paper the integration model that applies DEA on input data followed by the application of AI on the output of DEA models. The application of AI on DEA output relies on AI prompts that can ultimately enhance clinical decision based on fitness data. We explore the various approaches to develop libraries of AI prompts and implement a selected structure adapted to clinical decision based on fitness data analytics. This paper presents the selected DEA and AI integration model, the application of DEA models on

fitness data, and the library of AI prompts for clinical decision support based on fitness data analytics. The paper concludes with future enhancements by taking more fitness data and larger data sets and technology development of the library of AI prompts and autonomous AI agents for clinical decision based on fitness data.

The Selected Dea and AI Integration Model

Artificial Intelligence (AI) refers to the development of computational systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, perception, and language understanding. Currently, AI is evolving toward more sophisticated paradigms such as reinforcement learning, generative models, and agentic AI, which emphasize autonomy, adaptability, and decision-making in complex

environments. Artificial intelligence (AI) models and tools have evolved into a diverse ecosystem that underpins contemporary innovation across industries, research, and governance. At the core, AI models can be categorized into machine learning algorithms, deep learning architectures, and generative models, each designed to process data and produce insights or outputs with varying levels of complexity [4]. Data Envelopment Analysis (DEA) encompasses a wide range of models designed to measure efficiency under different assumptions, and several specialized software tools have been developed to implement these models effectively. The CCR model, introduced by Charnes, Cooper, and Rhodes, assumes constant returns to scale and is widely used when DMUs operate at optimal scale.

The BCC model, developed by Banker, Charnes, and Cooper, extends DEA to variable returns to scale, allowing separation of scale efficiency from pure technical efficiency [4]. The methodology

adopted in (Osman, et al., 2026a) [4] to integrate DEA and AI is based on the analysis of data input and output type and structure of both AI and DEA. DEA provides a structured, non-parametric framework for evaluating the relative efficiency of decision-making units by comparing multiple inputs and outputs, while AI models such as machine learning, deep learning, and generative approaches introduce predictive, adaptive, and non-linear capabilities. When DEA tools like OSDEA, deaR, or DEA Solver are combined with AI platforms such as TensorFlow, PyTorch, or Scikit-learn, organizations can move beyond static benchmarking toward dynamic, scenario-based optimization. Three integration models are identified based on the DEA and AI input and output sequences as shown in Figure 1 DEA followed by AI sequential input and output integration, Figure 2 DEA AND AI matrix input and output integration, and Figure 3 AI followed by DEA sequential input and output integration (Figure 1,2,3).

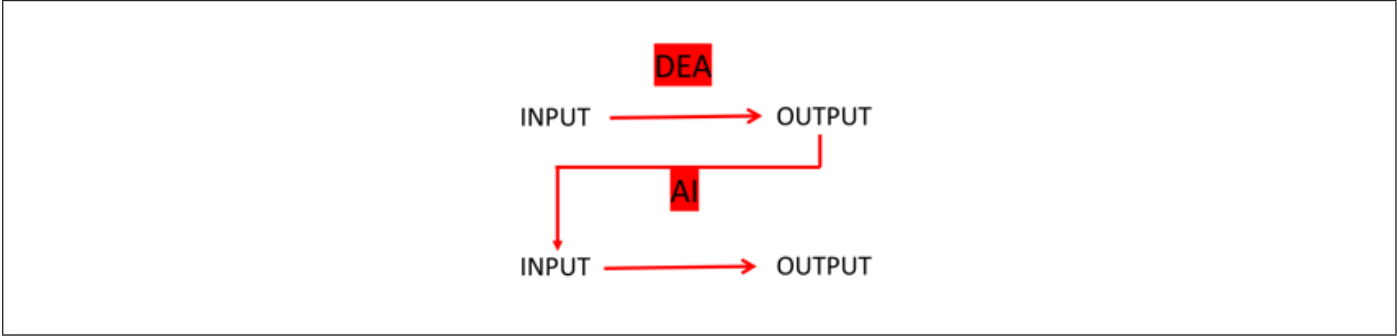


Figure 1: Integration Model 1, DEA followed by AI sequential input and output integration.

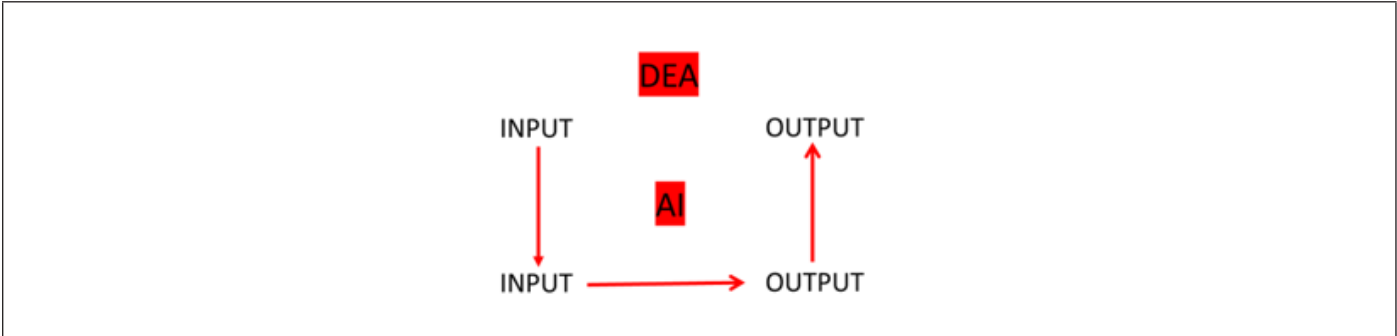


Figure 2: Integration Model 2, DEA AND AI matrix input and output integration.

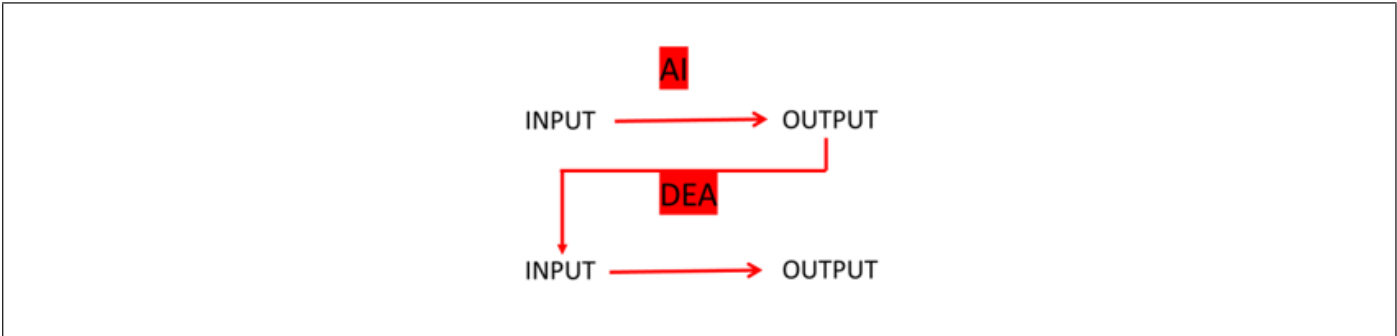


Figure 3: Integration Model 3, AI followed by DEA sequential input and output integration.

The Implementation of Integration Model 1

In this paper, we consider the first model of integration based on DEA followed by AI sequential input and output integration.

The input for DEA is fitness data. In *Osman, et al., (2026b) [3]*, fitness data structure was identified as:

1. User Profile

- Age, gender, height, weight, baseline health metrics.
- Used for calibration of calorie burn and VO_2 max estimates.

2. Activity Tracking

- Steps, distance, floors climbed, active minutes.
- Often stored as time-series data with timestamps.

3. Heart Rate

- Resting heart rate, max heart rate, HR variability.
- Continuous monitoring with 1–5 second intervals.

4. Sleep Data

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

- Structured as nightly logs with stage transitions.

5. Exercise Sessions

- Type of workout (running, cycling, swimming).
- Metrics: pace, cadence, elevation, GPS route.

6. Calories & Energy

- Active calories vs. basal metabolic rate.
- Linked to activity and heart rate data.

7. Environmental Sensors

- GPS coordinates, altitude, temperature, sometimes SpO_2 .
- Stored as geospatial + physiological datasets.

8. Export Formats

- Commonly JSON, CSV, or proprietary app databases.
- Structured with timestamps, sensor IDs, and units.

The output of DEA is a technical efficiency score which is used in AI prompts that can ultimately enhance clinical decision based on fitness data (Figure 4).

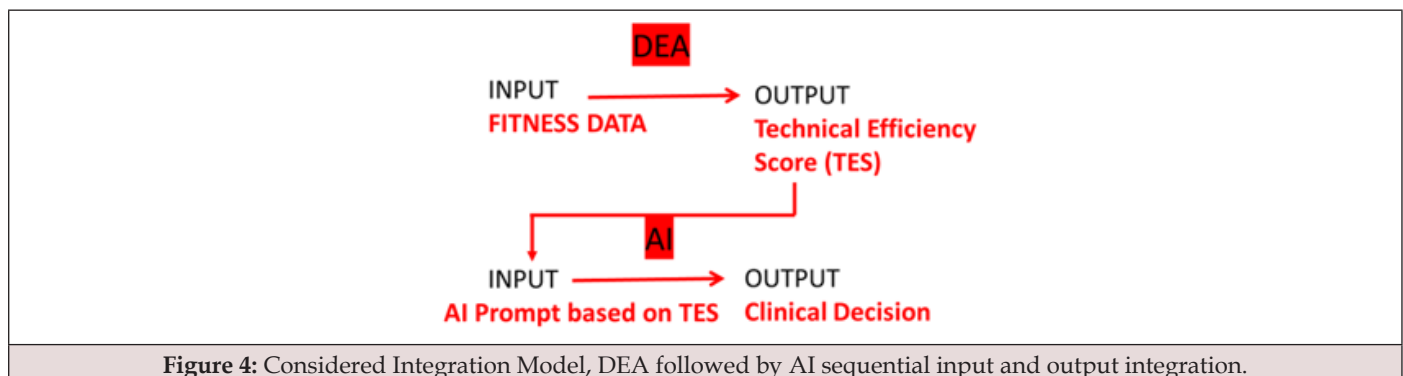


Figure 4: Considered Integration Model, DEA followed by AI sequential input and output integration.

The Application of Dea CCR and Bcc Models on Fitness Data

Data Envelopment Analysis (DEA) is a non-parametric method that evaluates the relative efficiency of Decision-Making Units (DMUs). DEA constructs an efficiency frontier based on the most efficient DMUs and measures the performance of others against this benchmark. 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 (*Oaman, et al., 2026b*).

Fitness Data Used

We consider fitness-band dataset for five persons and its corresponding DEA (Data Envelopment Analysis) input-output structure suitable for Excel Solver. Table 1 shows fitness data

collected from fitness band for five persons involving simple recording of walking activity. Recorded data are heart rate in beats per minute (bpm), steps, and walking distance (Table 1).

Using DEA Microsoft Excel Solver

Data Envelopment Analysis (DEA) is conducted in Excel using the Solver add-in. We solved the problem for both output-oriented and input-oriented models under Variable Returns to Scale (VRS/BCC) and Constant Returns to Scale (CRS/CCR) assumptions, considering constraints, objective functions, efficiency calculations, and interpretation of peer person with best health (heart beat per minute). The solver setup involved the installation and enabling Excel Solver to run DEA linear programming. In excel solver, the output Oriented VRS model maximizes output expansion factor ϕ to find technical efficiency. The Input Oriented CRS model in DEA solver involves minimizing θ to measure efficiency, removing sum

$\lambda=1$ constraint. The output-oriented DEA in Excel solver starts with defining lambda weights (initially zero), setting an initial ϕ (phi) value of 1, and calculating technical efficiency as $1/\phi$. The left-hand side of constraints is built using SUMPRODUCT between outputs or inputs and lambdas, while the right-hand side uses ϕ multiplied by the observed person's output (heart rate in beats per minute)

for outputs, and the observed person's inputs (steps and distance) for inputs. In Solver, the objective is to maximize ϕ by changing lambdas and ϕ , adding constraints for outputs ($\geq$), inputs ($\leq$), and under variable return to scale VRS the sum of lambdas equal to 1, with non-negativity enforced [6].

Table 1: Fitness Data Considered for five persons (Decision Making Units DMU in DEA).

Person (DMU)	DEA Output: Heart Rate (bpm)	DEA Input: Steps	DEA Input: Walking Distance (km)
Person 1	120	8,000	6.0
Person 2	115	7,500	5.5
Person 3	130	9,000	7.0
Person 4	110	7,000	5.0
Person 5	125	8,500	6.5

The difference between CRS (Constant Returns to Scale) and VRS (Variable Returns to Scale) in our example lies in the presence of the "sum of lambdas = 1" constraint. For VRS/BCC models, this constraint is included, ensuring variable returns to scale are modeled. To switch to CRS/CCR, we simply removed that constraint in DEA Excel Solver. This change alters the feasible region and can slightly adjust λ values and efficiency scores, reflecting the constant returns assumption. For input-oriented DEA, the process mirrors the output-oriented case but minimizes θ (theta) instead of maximizing ϕ . Technical efficiency equals θ , starting at 1, and constraints are

adjusted: the output constraint ensures weighted outputs $\geq$ the observed person's output, while the input constraint has weighted inputs $\leq \theta$ times the observed person's inputs. In DEA excel Solver, θ and lambdas are decision variables, the objective is minimization, and under VRS the sum of lambdas equals 1. Removing that yields the CRS version. Efficiency scores then indicate the proportion of current inputs needed to produce the same output. Using Excel DEA Solver we compute output-oriented DEA Technical Efficiency Score of a person producing output bundle y^θ (Calories) from the input bundle x^θ (steps, distance) (Figure 5).

$$\tau_j(x^0, y^0) = \frac{1}{\phi^*}$$

where

$$\begin{aligned} \phi^* &= \max \phi \\ \text{s.t. } \sum_{j=1}^N \lambda_j y^j &\geq \phi y^0; \\ \sum_{j=1}^N \lambda_j x^j &\leq x^0; \\ \sum_{j=1}^N \lambda_j &= 1; \\ \lambda_j &\geq 0, (j=1, 2, \dots, N); \phi \text{ unrestricted.} \end{aligned}$$

Figure 5: The computation of output-oriented DEA Technical Efficiency Score of a person producing output bundle y^θ (Calories) from the input bundle x^θ (steps, distance).

The DEA model for Microsoft Excel DEA solver involves an excel sheet of four columns. The first column is the person. The second column is the DEA output heart rate (bpm beats per minute)

considered as the Decision-Making Unit DMU. The third column is the DEA solver input number of steps. The fourth column is the DEA solver input walking distance (Table 2).

Table 2: Microsoft Excel sheet including fitness data to be processed with Excel Data Solver Initial Lambda is 0; Sum Lambda is 0; initial Phi is 1; Peer Person is Person D; The LHS Output is SUMPRODUCT of output multiplied by lambda and SUMPRODUCT of input multiplied by lambda, The RHS Output is Peer DMU output (Person D best heart performer) multiplied by the expansion factor Phi, the inputs are copied input of Peer DMU (Person D) inputs.

	A	B	C	D	E	F	G	H	I	J	K
1	Person	Output Heart Rate (bpm)	Steps	Distance	Lambda	Sum			Output	I	k
2	A	120	8,000	6	0	0		LHS	0	0	0
3	B	115	7,500	5.5	0	Phi		RHS	110	7000	5
4	C	130	9,000	7	0	1					
5	D	110	7,000	5	0	Tech Eff=1/ Phi					
6	E	125	8,500	6.5	0	1					

In this DEA formulation, each person represents a Decision-Making Unit (DMU). The output variable is the heart rate measured in beats per minute (bpm), while the input variables are the number of steps and the walking distance. The dataset is organized in four columns as required for Excel Solver implementation. Column A contains the DMU identifier (Person), Column B contains the output value (Heart Rate), Column C contains the first input (Steps), and Column D contains the second input (Walking Distance).

The table is used as the basis for an input-oriented and output-oriented DEA model using Excel Solver, where efficiency scores are calculated by comparing each person's heart-rate output against the resources consumed in terms of steps taken and walking distance. The choice of peer DMU is based on DEA efficiency concept where a higher output (heart rate) is obtained with lower inputs (steps

and walking distance). We selected the peer DMU based on a basic output-to-input ratio of efficiency calculation:

$$\text{Efficiency} = \text{Heart Rate} / \text{Steps} \times \text{Distance}$$

$$\text{Efficiency} = \frac{\text{Heart Rate}}{\text{Steps} \times \text{Distance}}$$

Based on this simple DEA-style efficiency measure, Person 4 is the best performer, achieving a heart rate of 110 bpm while using the lowest inputs (7,000 steps and 5 km walking distance), resulting in the highest efficiency score of 3.14. Person 2 ranks second with an efficiency score of 2.79, followed by Person 1, Person 5, and Person 3 (Table 3).

Table 3: Selected Peer DMU (PERSON4 with best fitness data).

Person	Heart Rate	Steps	Distance (km)	Simple Efficiency Score ($\times 10^6$)
Person 1	120	8000	6.0	2.50
Person 2	115	7500	5.5	2.79
Person 3	130	9000	7.0	2.06
Person 4	110	7000	5.0	3.14
Person 5	125	8500	6.5	2.26

DEA compares each DMU against the others to determine which one is the most efficient in converting inputs into outputs. The Decision-Making Units (DMUs) are the five individuals participating in the walking activity. Each DMU consumes two inputs, namely the number of steps and walking distance, to produce one output, namely heart rate measured in beats per minute (bpm). DEA compares the relative efficiency of these individuals and identifies the efficient frontier consisting of the best-performing DMUs. The Heart Rate (HR) measured in beats per minute (bpm) can provide a simple indication of cardiovascular fitness, especially when measured during a standardized walking activity. In general, a lower heart rate while performing the same

walking workload suggests better cardiovascular efficiency because the heart requires fewer beats to supply oxygen to the body. For a moderate walking exercise, a heart rate below 100 bpm is typically associated with good fitness, a heart rate between 100 and 120 bpm is generally acceptable and indicates average fitness, while a heart rate consistently above 120 bpm during the same activity may indicate lower fitness, deconditioning, excessive exertion, or potential health concerns. However, heart rate should always be interpreted in conjunction with age, fitness level, medication use, and medical history. Persistent unusually high or low heart rates should be assessed by a healthcare professional (Table 4,5).

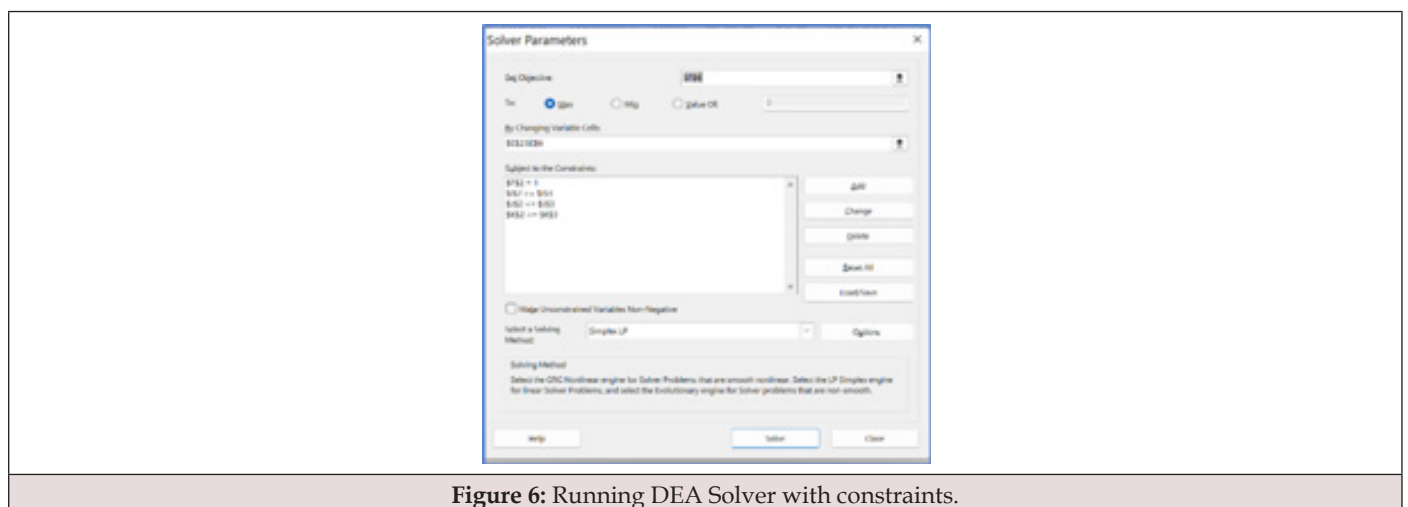
Table 4: Fitness Level based on heart rate (beats per minute bpm).

Heart Rate During Walking (bpm)	Fitness Assessment	Interpretation	Recommended Action
< 100	Good	Efficient cardiovascular response to walking	Continue current fitness routine
100-120	Acceptable	Average fitness and normal exercise response	Maintain or gradually improve activity level
121-140	Fair/Poor	Higher effort required for the same activity	Increase aerobic exercise and monitor progress
> 140	Poor / Potential Concern	May indicate low fitness, excessive exertion, or underlying condition	Medical evaluation recommended if persistent
< 50 (not an athlete)	Potential Concern	Abnormally low heart rate for most adults	Medical evaluation recommended

Table 5: Fitness level of DMUs applying criteria for heart rate fitness level.

DMU (Person)	Heart Rate (bpm)	Fitness Category
Person 1	120	Acceptable
Person 2	115	Acceptable
Person 3	130	Fair/Poor
Person 4	110	Acceptable (Best among this group)
Person 5	125	Fair/Poor

Based solely on heart rate during the walking activity, Person 4 (110 bpm) demonstrates the best cardiovascular response among the five participants, followed by Person 2 (115 bpm) and Person 1 (120 bpm). Persons 3 and 5 exhibit higher heart rates for a similar activity and may have comparatively lower cardiovascular fitness (Figure 6).

**Figure 6:** Running DEA Solver with constraints.

AI Prompts Applied to Dea Output for Enhanced Clinical Decision

DEA Solver is used to calculate efficiency scores for patients, AI uses the DEA outputs to generate clinical insights, risk assessments, and personalized recommendations. The DEA score is a feature that helps the AI distinguish between individuals who achieve good physiological outcomes with relatively low resource utilization and those who may require intervention. Various AI prompts can be structured based on DEA output. A sample set of AI prompts based on DEA output is presented in Table 5.

An advanced prompt for an AI-enhanced Clinical Decision Support System (CDSS) could be:

“Analyze the patient’s DEA efficiency score, heart rate, steps, walking distance, age, BMI, blood pressure, and previous fitness records. Compare the patient with efficient peer DMUs identified by DEA. Classify fitness status, identify potential cardiovascular risks, explain the factors contributing to inefficiency, and generate personalized recommendations for exercise, lifestyle modification, and follow-up monitoring. Present the results as a clinical report with risk level, explanation, and intervention plan.”

Table 5: AI prompts based on DEA output.

Clinical Decision Objective	AI Prompt
Efficiency Interpretation	"Analyze the DEA efficiency score of Patient 4 (1.00) based on heart rate, steps, and walking distance. Explain why this patient is considered efficient compared with peer patients."
Patient Risk Assessment	"Given a DEA efficiency score of 0.72, heart rate of 130 bpm, 9,000 steps, and 7 km walking distance, assess the patient's cardiovascular fitness risk level and provide a clinical interpretation."
Clinical Recommendation	"Using the DEA efficiency score and fitness-band data, generate evidence-based recommendations to improve cardiovascular fitness over the next 12 weeks."
Population Benchmarking	"Compare Patient 3 against the efficient frontier patients identified by DEA and explain the performance gap and potential clinical causes."
Early Warning System	"Review DEA efficiency scores below 0.80 and identify patients requiring further cardiovascular assessment or preventive intervention."
Personalized Exercise Plan	"Based on a DEA efficiency score of 0.75 and elevated walking heart rate, generate a personalized walking and aerobic exercise program."
Clinical Decision Support	"Act as a clinical decision support system. Use DEA efficiency, heart rate, steps, walking distance, age, and BMI to classify patient fitness as Good, Acceptable, Poor, or Requires Medical Evaluation."
Trend Analysis	"Analyze DEA efficiency scores over the last six months and determine whether the patient's cardiovascular condition is improving, stable, or deteriorating."
Explainable AI Report	"Generate an explainable clinical report showing the factors contributing most to the patient's DEA inefficiency and provide corrective actions."
Preventive Care Recommendation	"Identify patients with declining DEA efficiency and recommend preventive interventions before cardiovascular risks become significant."

Building The Library of AI Prompts

A Library of AI Prompts for Clinical Decision Support (CDS) based on fitness data and Data Envelopment Analysis (DEA) can be viewed as a knowledge-driven architecture that systematically organizes, stores, retrieves, and executes clinical prompts using wearable-device measurements and DEA-derived efficiency indicators. The objective of this architecture is to transform raw fitness and physiological data into explainable recommendations that support clinicians, patients, and healthcare organizations. DEA provides objective efficiency benchmarking, while AI converts efficiency measurements into actionable clinical insights and personalized interventions [5,7].

Architecture Layer 1: Data Acquisition Layer

The first layer collects data from wearable and clinical sources. Fitness bands, smart watches, mobile health applications, and electronic health records continuously generate physiological and behavioral measurements including heart rate, step count, walking distance, sleep duration, blood oxygen saturation, energy expenditure, and other health indicators. The purpose of this layer is to provide reliable and continuous data streams that support health monitoring and clinical analysis. Modern digital health strategies emphasize the importance of utilizing digital technologies and health data to support informed healthcare decisions and improve patient outcomes (Digital health).

Architecture Layer 2: Data Management and Integration Layer

The second layer integrates wearable-device data with healthcare information systems. Data are standardized, cleaned,

validated, and stored in secure databases. Interoperability can be achieved using standards such as HL7 FHIR, allowing data exchange between wearable platforms, hospital systems, and electronic health records. This layer ensures that fitness and clinical information are available in a consistent format for subsequent analytics and AI processing. The quality and interoperability of healthcare data are critical factors for successful AI-supported healthcare applications (Supporting AI in Healthcare).

Architecture Layer 3: DEA Analytics Engine

The DEA Analytics Engine constitutes the core analytical component of the architecture. DEA evaluates the relative efficiency of individual patients or wearable-device users by comparing multiple inputs and outputs simultaneously. In a fitness context, inputs may include steps, walking distance, exercise duration, and calories consumed, while outputs may include desirable health outcomes such as improved cardiovascular performance or reduced recovery time. DEA identifies efficient individuals that form the best-practice frontier and assigns efficiency scores to all participants. These efficiency scores provide an objective measure of health-performance effectiveness and serve as important inputs to AI reasoning processes [2,7].

Architecture Layer 4: Clinical Knowledge and Prompt Repository

This layer contains the AI Prompt Library itself. The repository stores reusable prompt templates categorized according to clinical objectives such as cardiovascular assessment, chronic disease monitoring, rehabilitation, preventive care, lifestyle intervention, patient coaching, and risk prediction. Each prompt

follows a standardized structure containing patient demographics, wearable measurements, DEA efficiency scores, benchmark patient information, clinical objectives, expected outputs, and explainability requirements. The repository functions as an organizational knowledge base that enables healthcare professionals to reuse validated prompts instead of developing new prompts for every clinical scenario. Such standardization enhances consistency, reproducibility, and quality of AI-generated outputs.

Architecture Layer 5: AI Reasoning and Decision Engine

The AI Reasoning Engine utilizes large language models and machine-learning algorithms to execute prompts retrieved from the library. The engine combines clinical variables with DEA analytics to produce recommendations, explanations, alerts, and intervention plans. For example, an AI prompt may instruct the system to analyze a patient with a DEA efficiency score of 0.75, elevated heart rate during walking, and increasing cardiovascular workload. The AI engine can interpret these indicators and generate personalized recommendations regarding exercise intensity, risk management, and medical follow-up.

1.1. Architecture Layer 6: Clinical Decision Support Layer

The Clinical Decision Support Layer presents AI-generated recommendations to clinicians and patients. Outputs may include risk classifications, patient summaries, intervention recommendations, health-performance comparisons, alerts, and follow-up plans. The layer acts as the interface between AI systems and end users, enabling healthcare professionals to incorporate AI-supported recommendations into clinical practice. Clinical decision support functionality aligns with recommendations that digital health technologies should support health workers, improve decision-making quality, and strengthen healthcare delivery systems [9].

Architecture Layer 7: Learning and Continuous Improvement Layer

The final layer supports continuous improvement of the prompt library and AI models. Outcomes generated from clinical interventions can be collected and evaluated to determine the effectiveness of individual prompts. Prompt performance analytics can identify highly successful prompt templates, allowing the repository to evolve over time. New wearable metrics, clinical evidence, and AI capabilities can also be incorporated into the architecture, creating a continuously learning clinical decision-support ecosystem.

Architectural Flow

The overall architecture follows a sequential workflow. Fitness bands and clinical systems generate data that are integrated and standardized within healthcare databases. DEA analytics calculate efficiency scores and identify benchmark patients. The Clinical

Knowledge and Prompt Repository selects appropriate prompt templates based on patient conditions and clinical objectives. The AI Reasoning Engine executes these prompts by combining fitness data, DEA outputs, and clinical knowledge. The Clinical Decision Support Layer delivers personalized recommendations to clinicians and patients, while the Learning Layer continuously improves prompt quality and system performance.

Conclusion and Future Work

The proposed framework for building a library of AI prompts based on fitness data and Data Envelopment Analysis (DEA) provides a structured approach for enhancing Clinical Decision Support Systems (CDSS). By integrating wearable-device measurements such as heart rate, step count, and walking distance with DEA efficiency analytics, healthcare organizations can transform raw fitness data into meaningful indicators of patient performance and health status. DEA contributes objective benchmarking capabilities by identifying efficient and inefficient individuals relative to their peers, while AI converts these analytical insights into personalized recommendations, risk assessments, and explainable clinical narratives. This combination addresses one of the major challenges in digital healthcare, namely the transformation of large volumes of health data into actionable clinical knowledge. Studies have shown that DEA is an effective method for healthcare performance evaluation and benchmarking, while hybrid DEA-AI approaches offer significant opportunities to improve decision support and predictive capabilities [1,5,7]. Furthermore, the AI prompt library serves as a reusable knowledge framework that standardizes interactions between healthcare professionals and AI systems. Rather than relying on ad hoc prompt creation, clinicians can use validated prompt templates tailored to specific healthcare objectives such as cardiovascular risk assessment, patient monitoring, preventive care, rehabilitation, and lifestyle intervention. The resulting system promotes consistency, explainability, and transparency in clinical decision-making, which are critical requirements for successful adoption of AI in healthcare environments. The importance of explainable and trustworthy AI for clinical decision support has been emphasized in recent healthcare research and digital health initiatives [8,9].

Future research should focus on expanding the range of wearable-derived health indicators incorporated into the DEA-AI framework. In addition to heart rate, steps, and walking distance, future implementations may include sleep quality, heart-rate variability, blood oxygen saturation, respiratory rate, stress measurements, caloric expenditure, and other physiological metrics available through modern wearable technologies. Such multidimensional data could improve the accuracy and comprehensiveness of DEA efficiency assessments and AI-generated clinical recommendations [7]. Further investigation is also needed into dynamic and longitudinal DEA models that can evaluate changes in patient efficiency over time. Most current

DEA applications provide a static assessment based on a single observation period. Future systems could continuously monitor patient progress and detect early signs of health deterioration, thereby supporting preventive interventions and personalized healthcare planning. The integration of longitudinal DEA analytics with predictive machine learning models may further enhance the ability of healthcare providers to identify future risks and proactively manage patient health [1].

Another important area for future work is explainable AI and clinical transparency. Future prompt libraries should incorporate explainability mechanisms that clearly describe how DEA efficiency scores, physiological indicators, and clinical variables contribute to recommendations. Such transparency is essential for clinician trust, regulatory compliance, and patient acceptance. Research indicates that healthcare professionals prefer AI systems that provide concise explanations, contextual information, and actionable recommendations rather than unexplained predictions [8]. Future implementations should investigate integration with Electronic Health Records (EHRs), HL7 FHIR interoperability standards, telemedicine platforms, and population-health management systems. The combination of DEA analytics, wearable technologies, AI-driven prompt libraries, and interoperable healthcare infrastructures could support real-time monitoring, personalized interventions, and large-scale preventive healthcare programs. Such developments align closely with global digital-health strategies that emphasize the use of digital technologies to improve healthcare quality, efficiency, and accessibility [9,10].

Acknowledgement

We would like to thank Prof Yusuf Sidani, Dean of Olayan School of Business at the American University of Beirut, for his help and support. His invaluable input and continuous support and encouragement to proceed forward helped us to carry on with this research to spread knowledge and advance research and development in Artificial Intelligence, DEA, and primary care.

Conflict of Interest Statement

There is no conflict of interest.

Funding Statement

This research is funded by Olayan School of Business at the American University of Beirut.

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