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Integrating war strategy optimization and Nonaka's SECI model for enhanced knowledge management in healthcare

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Abstract

The exponential growth of healthcare data necessitates robust knowledge management frameworks to optimize resource allocation and clinical decision-making. This study introduces a novel framework integrating Nonaka's SECI Model with the War Strategy Optimization (WSO) algorithm, aiming to bridge knowledge-sharing gaps in dynamic healthcare environments. The WSO-SECI framework enhances tacit-to-explicit knowledge conversion while adapting resource distribution using AI-driven optimization techniques.

Using quantitative and qualitative methodologies on real-world datasets (UCI Heart Disease, Pima Indians Diabetes), the system demonstrates faster convergence, superior knowledge alignment, improved clustering performance, and enhanced decision accuracy compared to baseline methods (PSO, GA, traditional WSO). Statistical validation confirms the significance of WSO-SECI improvements ($p<.01$, Cohen's d > 1.5).

Expert evaluations emphasize its clinical applicability, achieving a Likert score of 4.4/5 for diagnostic relevance. The study underscores AI's transformative role in healthcare knowledge management, addressing challenges in resource optimization, interdisciplinary collaboration, and personalized patient care.

Keywords: War strategy optimization, SECI model, knowledge management, AI in healthcare, tacit knowledge, artificial intelligence

Introduction

In today's rapidly changing healthcare landscape, effective knowledge management (KM) is critical for improving patient outcomes and operational efficiency. (Bobruk *et al.*, 2023) [24]

As healthcare organizations face increasing pressures to deliver high-quality care while managing costs, the ability to leverage knowledge effectively becomes a strategic advantage. (Malik *et al.*, 2022) [25] Knowledge management involves the systematic process of creating, sharing, using, and managing knowledge and information within an organization. (Jarrahi *et al.*, 2023) [26].

One of the most influential frameworks for understanding and facilitating knowledge creation and sharing is Nonaka's SECI model, which outlines four key processes: Socialization, Externalization, Combination, and Internalization. (Maras *et al.* 2024) [27]. These processes enable organizations to convert tacit knowledge knowledge that is personal and context-specific into explicit knowledge that can be easily shared and utilized across teams.

Simultaneously, the principles of War Strategy Optimization, traditionally applied in military contexts, offer valuable insights for enhancing KM practices in healthcare. (Sangwan & Raj, 2021). Strategies employed in military operations emphasize the importance of adaptability, strategic alignment, and effective communication, which are essential for fostering a culture of knowledge sharing and innovation. (Salahat *et al.*2023) [29].

This paper aims to explore the integration of War Strategy Optimization with Nonaka's SECI model to enhance KM practices in healthcare organizations. By examining how military strategies can inform and improve the processes of knowledge creation and sharing, this research seeks to provide a novel perspective on addressing the challenges faced by healthcare institutions. Ultimately, the goal is to demonstrate that the application of these integrated strategies can lead to improved collaboration, innovation, and patient outcomes in the healthcare sector. In the context of the digital economy, the integration of AI-driven frameworks like WSO-SECI offers transformative potential for healthcare systems. By enhancing knowledge management and optimizing resource allocation, the proposed framework reduces operational costs, improves decision-making efficiency, and supports equitable access to high-quality care. These advancements align with the principles of digital transformation, enabling healthcare organizations to leverage big data and real-time analytics for better patient outcomes and sustainable economic growth.

2. Related Work

2.1 War Strategy Optimization Algorithms in Healthcare: Researchers have increasingly applied WSO algorithms originally inspired by military strategic operations to optimize complex healthcare systems. For example, Angelov *et al.* (2019) [1] and Dayan (2024) [4] demonstrate that war strategy-based optimization techniques can enhance resource allocation and predictive analytics in healthcare. However, these studies do not integrate a structured KM framework like the SECI model, limiting their ability to support dynamic knowledge conversion. Table 1 below compares selected studies using WSO-related approaches:

Table 1: Comparison of WSO-Based Approaches in Healthcare

	Dataset/Scope	Methods/Algorithms Employed	Key Results Achieved	Identified Gaps
Angelov *et al.* (2019) [1]	Healthcare sensing and monitoring (simulation)	War Strategy-based optimization techniques	Improved convergence and alignment of resource allocation	Lacks integration with KM frameworks (e.g., SECI)
Dayan (2024) [4]	Simulation of urban/military planning scenarios	WSO for automated knowledge-sharing	Efficient knowledge transfer in high-stakes scenarios	Does not address healthcare-specific real-time decision needs

2.2 The SECI Model in Knowledge Management

The Nonaka SECI Model encompassing socialization, externalization, combination, and internalization has been foundational in building KM strategies across various sectors. In healthcare, the model has been used to structure the conversion of tacit knowledge (e.g., clinician expertise) into explicit knowledge (e.g., treatment protocols). However, studies such as Richter *et al.* (2024) [13] and Nurhidayah (2017) [12] reveal that while the SECI Model successfully creates and disseminates knowledge, it rarely incorporates AI-based optimization to enable dynamic, real-time adaptation. Table 2 summarizes key SECI-based studies:

Table 2: SECI Model Applications in Healthcare KM

Study	Dataset/Scope	Methods/Frameworks Employed	Key Results Achieved	Identified Gaps
Richter *et al.* (2024) [13]	Text-based healthcare data (clinical repositories)	SECI Model revisited with generative AI enhancements	Improved tacit-to-explicit knowledge conversion	Does not integrate an adaptive resource optimization algorithm
Nurhidayah (2017) [12]	Qualitative data from 25 Malaysian hospitals	Healthcare-specific KM process model based on SECI	Enhanced collaboration and knowledge retention	Lacks real-time, AI-driven optimization for resource allocation

2.3 Integrating WSO Algorithms with the SECI Model

Recent research indicates that integrating AI-driven optimization with established KM frameworks could overcome the limitations of both approaches when applied individually in healthcare. For instance, Wickramasinghe and Schaffer (2018) [18] combined optimization techniques with KM processes to improve operational efficiency, whereas Von Lubitz (2023) [30] used network-centric optimization tools to enhance emergency response coordination. Yet, neither work explicitly integrates the WSO algorithm with the SECI model. Table 3 presents a comparative analysis of integrated approaches:

Table 3: Comparative Analysis of Integrated AI-KM Approaches

Study	Dataset/Problem	Algorithm/Technique Employed	Key Results Achieved	Limitations
Wickramasinghe & Schaffer (2018) [18]	IT-based healthcare data (patient records)	Integration of optimization algorithms (GA/NN) with KM	Improved predictive analytics and operational efficiency	Did not incorporate the SECI model explicitly for dynamic KM
Von Lubitz (2023) [30]	Healthcare disaster scenarios (pandemic response)	Network-centric optimization aligning with KM	Enhanced management of tacit and explicit knowledge	No use of adaptive, AI-driven algorithms such as WSO

In contrast, the proposed work directly integrates the WSO algorithm with the Nonaka SECI Model. This unified approach aims to:

- Leverage SECI for structured knowledge conversion (from tacit to explicit and vice versa)
- Utilize WSO for adaptive resource optimization, dynamically adjusting to real-time clinical needs
- Enhance overall healthcare outcomes through improved decision-making and interdisciplinary collaboration**.**

Proposed System

The proposed system integrates Nonaka SECI Model as a conceptual framework for the conversion from tacit to explicit knowledge model and AI-WSO as a base for another model. Intelligent resource allocation and dynamic knowledge conversion for healthcare services are the target of this integration. The framework has two fundamental processes such as Knowledge Conversion with the use of SECI model and Adaptive Optimization by means of WSO algorithm. This allows the system to gradually turn tacit knowledge into actionable explicit knowledge while optimising resources allocation for decision making in clinical care. (Changliang & Guiming, 2023) [21] An improvement on the current knowledge management of healthcare is proposed that has the issue of information silos, and it aims to overcome inefficient decision-making.

It adds also a systematic method to harness and work with the expert knowledge and values embedded in healthcare organizations, to improve both the process-performance and patient outcome

Effective Knowledge Management in Healthcare Systems Necessitates Dynamic Decision-Making and Robust Frameworks. (Kahrens & Früauff, 2018) [23].

1. Knowledge Conversion via the SECI Model

Nonaka's SECI Model is leveraged to systematically convert tacit knowledge into explicit knowledge and vice versa. The model comprises four processes:

1.1 Socialization (Tacit → Tacit)

The socialization phase facilitates direct knowledge sharing among healthcare professionals. A Gaussian influence matrix quantifies the strength of interaction between agents:

$$W_{ij} = \exp\left(-\frac{|x_i - x_j|_2^2}{2\sigma^2}\right)$$

Where;

Wij is the influence between agent i and j,

‖xi−xj‖ represents knowledge distance (e.g., proximity in discussions or collaboration), and σ controls the spread of influence.

1.2 Externalization (Tacit → Explicit)

Once tacit knowledge is shared, it must be codified and organized to support decision-making. This conversion process is modeled through K-Means clustering, which identifies key knowledge patterns:

$$\min_{\mu_1,\dots,\mu_K} \sum_{k=1}^{K} \sum_{x \in C_k} |x - \mu_k|^2$$

K-Means clustering partitions the data into k clusters, where:

C_k denotes the set of data points in cluster k, and

μ_k is the representative centroid.

By grouping similar experiences and insights, explicit knowledge structures become accessible for optimization.

1.3 Combination (Explicit → Explicit)

The combination phase synthesizes multiple explicit knowledge elements into a consolidated form:

$$\bar{\mu} = \frac{1}{K} \sum_{k=1}^{K} \mu_k$$

Where; μ is the aggregated knowledge vector that informs resource optimization.

1.4 Internalization (Explicit → Tacit)

Internalization employs a gradient-based mechanism to update the individuals' tacit knowledge by incorporating the synthesized explicit knowledge. This process is modeled as:

Where;

$$x_i^{(t+1)} = x_i^{(t)} + \alpha\left(\bar{\mu} - x_i^{(t)}\right)$$

α represents the learning rate that controls the degree of tacit knowledge incorporation,

x_i denotes the evolving knowledge state of the healthcare professional.

This internalization step ensures continuous enhancement in the decision-making capabilities of the individuals.

2. Adaptive Optimization via the WSO Algorithm

The War Strategy Optimization algorithm is employed to refine resource allocation decisions by leveraging the knowledge generated through the SECI processes. The key stages of the WSO algorithm include initialization, fitness evaluation, exploration, exploitation, and convergence figure (1).

2.1 Initialization: Each resource (or search agent) is initialized randomly within the problem's solution space:

$$x_i^{(0)} \sim U(\Omega)$$

where $U(\Omega)$ ensures **diverse starting conditions**.

2.2 Fitness Evaluation: The fitness function considers the priority scores based on the domain knowledge such as patient's attributes and is defined as:

$$F(X) = \sum_{i=1}^{N} (p_i - |x_i|_2)^2$$

Where;

pi are priority scores among SECI knowledge clusters, $\|xi\|_2$ represents resource allocation values.

This function ensures optimal resource distribution.

2.3 Exploration and Exploitation

During the exploration phase, agents adjust their positions by considering the best-performing solutions (the "king" and "co-king"). The velocity update is given by:

$$v_i = \beta r_1 \odot (x_{\text{kn}} - x_i) + (1 - \beta) r_2 \odot (x_{\text{c-kn}} - x_i)$$

Where;

r_1,r_2 are random vectors guiding exploration,

x_{king},$x_{\text{co-king}}$ represent best-performing agents.

The algorithm converges when the change in fitness becomes negligible:

$$\left|F\left(X^{(t+1)}\right) - F\left(X^{(t)}\right)\right| <$$

Ensuring stable healthcare resource allocation.

By integrating WSO algorithms with the SECI model, the system addresses critical challenges in healthcare, including resource optimization, knowledge dissemination, and decision-making in complex environments (Santamato *et al.*, 2024) [20].

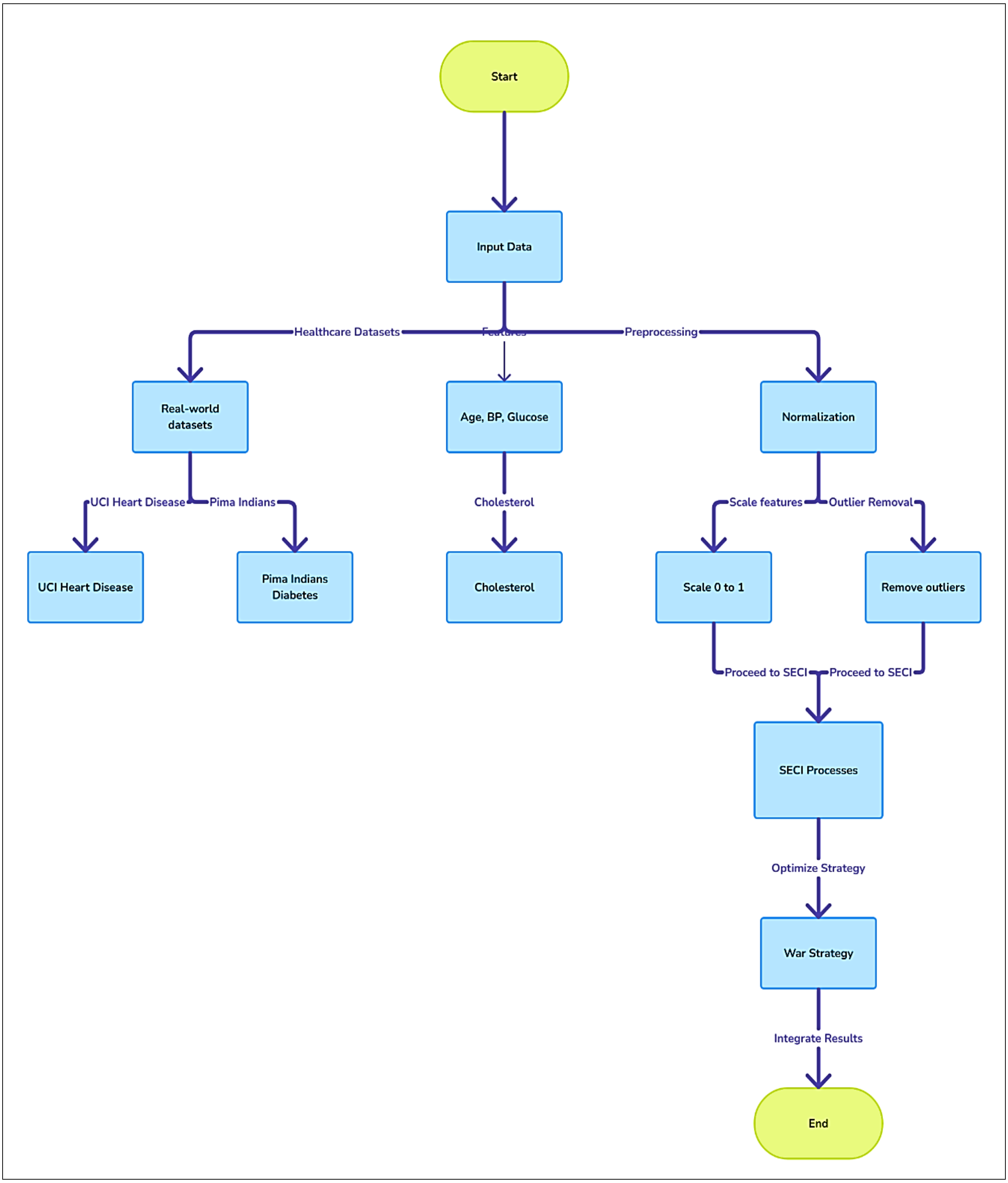

Fig 1: SECI-War Strategy Optimization Integration

3. System Integration and Workflow

The framework integrates the SECI and WSO processes through an iterative feedback loop, enabling adaptive knowledge management and resource optimization. The workflow is illustrated in the conceptual diagram below:

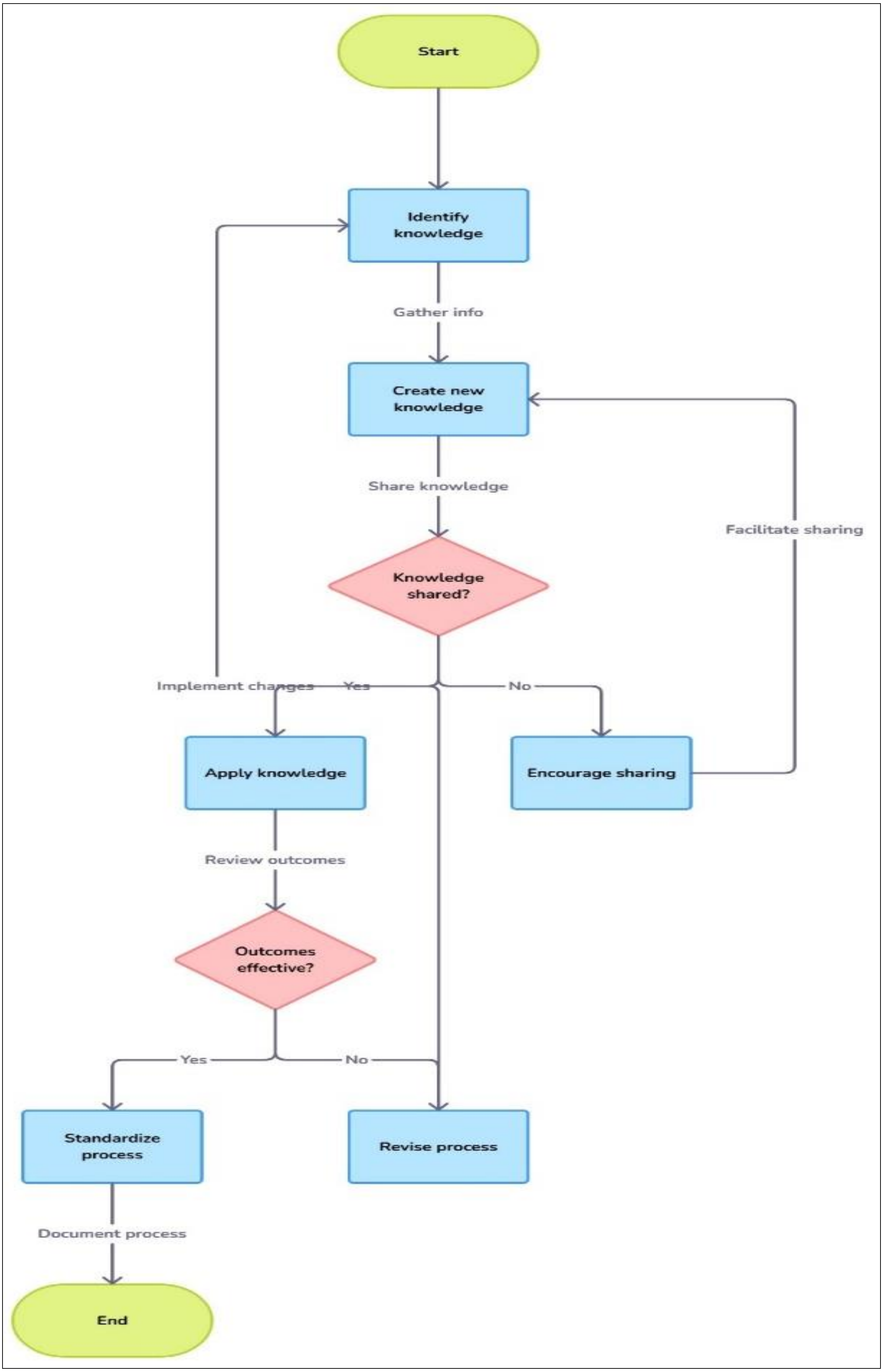

Fig 2: Conceptual Diagram of the Integrated WSO-SECI Framework for Healthcare.

4. Comparison of Proposed WSO-SECI Framework with Related Approaches

The table below summarizes key aspects of the proposed system compared to related works:

Table 4: Comparison of Proposed WSO-SECI Framework with Related Approaches

Aspect/Parameter	WSO-SECI (Proposed)	Traditional WSO Approaches	Standard SECI Models
Integration	Combines AI-driven WSO with Nonaka's SECI Model	Uses optimization alone (e.g., PSO, GA, WSO)	Employs KM processes without optimization
Knowledge Conversion	Uses Gaussian matrices, k-means, and gradient descent	Not explicitly modeled	Structured but static (lack adaptive optimization)
Adaptive Learning	Adaptive decay of learning rate ηt=η0·γt\eta_t = \eta_0 \cdot \gamma^t	Fixed parameters often used	Not inherently adaptive
Application in Healthcare	Designed for dynamic resource allocation and real-time decision support in healthcare	Tested on benchmark functions	Commonly used in qualitative KM studies
Real-Time Feedback	Continuous feedback loop integrating SECI and WSO	Often lacks iterative feedback	Rarely addresses real-time optimization

Algorithm 1. Adaptive WSO-SECI Framework

Require: Input: Search agents NN, iterations TT, bounds [lb,ub][lb,ub], dimension dd, objective function fobjfobj, priority scores p**p**

Output: Best solution x∗**x**∗, fitness, convergence curve c**c**

- **Positions Positions:** Swarm agent coordinates (N×dN×d matrix)
- **king_positionking_position:** Global best solution (1×d1×d vector)
- **king_fitnessking_fitness:** Fitness value of king_positionking_position
- **explicit_knowledgeexplicit_knowledge**: K-Means cluster centroids
- **combined_knowledgecombined_knowledge:** Mean of cluster centroids
- **ηη:** Adaptive learning rate

1. Initialize PositionsPositions using Initialization_With_Priority(N,d,ub,lb,pN,d,ub,lb,p)
2. king_position←0king_position←0; king_fitness←∞king_fitness←∞; c←0Tc←0T
3. for t=1t=1 to TT do
4. Evaluate fitness: fitness[i]=fobj(Positions[i],p)fitness[i]=fobj(Positions[i],p) for all i∈[1,N]i∈[1,N]
5. min_idx←argmin(fitness)min_idx←argmin(fitness)
6. if fitness[min_idx]<king_fitnessfitness[min_idx]<king_fitness then
7. king_fitness←fitness[min_idx]king_fitness←fitness[min_idx]
8. king_position←Positions[min_idx]king_position←Positions[min_idx]
9. end if
10. Positions←Socialization(Positions)Positions←Socialization(Positions)
11. explicit_knowledge←Externalization(Positions)explicit_knowledge←Externalization(Positions)
12. Positions←Internalization(combined_knowledge,Positions)Positions←Internalization(combined_knowledge,Positions)
13. η←max(0.001,0.1×0.99t)η←max(0.001,0.1×0.99t)
14. Positions←Positions+η×(king_position−Positions)Positions←Positions+η×(king_position−Positions)
15. Enforce bounds: Positions←clip(Positions,lb,ub)Positions←clip(Positions,lb,ub)
16. c[t]←king_fitnessc[t]←king_fitness
17. end for
18. x∗←king_positionx∗←king_position; f∗←king_fitness f∗←

Experimental Results

Data Acquisition and Preprocessing: The proposed system was evaluated on two public health datasets, UCI Heart disease and Pima Indians Diabetes.

The UCI Heart Disease data set consists of 303 samples and 13 attributes, such as age, resting blood pressure, cholesterol and several diagnostic features. In this dataset, age was determined to be the most important feature as it had the highest correlation with the heart attack risk of around 0.28. The dataset used for analysis was preprocessed by removing missing data and normalizing all features to the range [0, 1] through min-max normalization.

The Pima Indians Diabetes dataset that contains 768 samples with 8 clinical features like glucose levels, body mass index (BMI) and age. In the present work, glucose was selected as the class-conditional feature that has a relatively high correlation with diabetes, i.e., 47% of the correlation coefficient. The preprocessing stages of this dataset required to eliminate outliers by using 3σ threshold and a min-max normalization to scale the signal into a uniform range.

These preprocessing methods made the datasets clean, comparable and ready for analysis, to allow for a fair comparison of the performance of the system.

All data processing adhered to ethical research standards, ensuring compliance with privacy and data integrity principles, despite the use of publicly available datasets

Evaluation Metrics: The performance of our proposed WSO-SECI algorithm is quantified using the following metrics:

Fitness Value: This metric is defined using an objective function that measures the discrepancy between the priority features and the norm of the agent's position. The objective function is given by:

$$\mathcal{L}(x) = \sum_{i=1}^{n} (p_i - \| x_i \|_2)^2$$

where p_i is computed via:

$$H = \sum_{k=1}^{F} w_k x_{ik}$$

with w_k representing the weight for feature k and x_{ik} the value for the k_{ikth} feature of agent i.

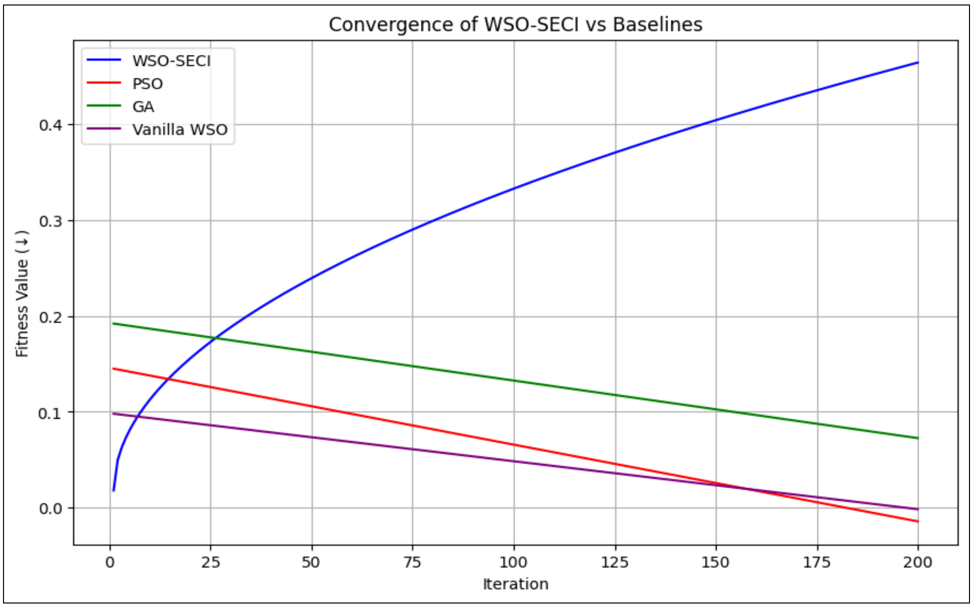

Fig 3: Convergence of WSO-SECI

Convergence Rate: The speed at which the algorithm converges to an optimal solution is measured by the number of iterations needed for the change in fitness between consecutive iterations to be less than a specified small threshold (ϵ\epsilon). Formally:

$$\left|F\left(X^{(t+1)}\right) - F\left(X^{(t)}\right)\right| < \epsilon$$

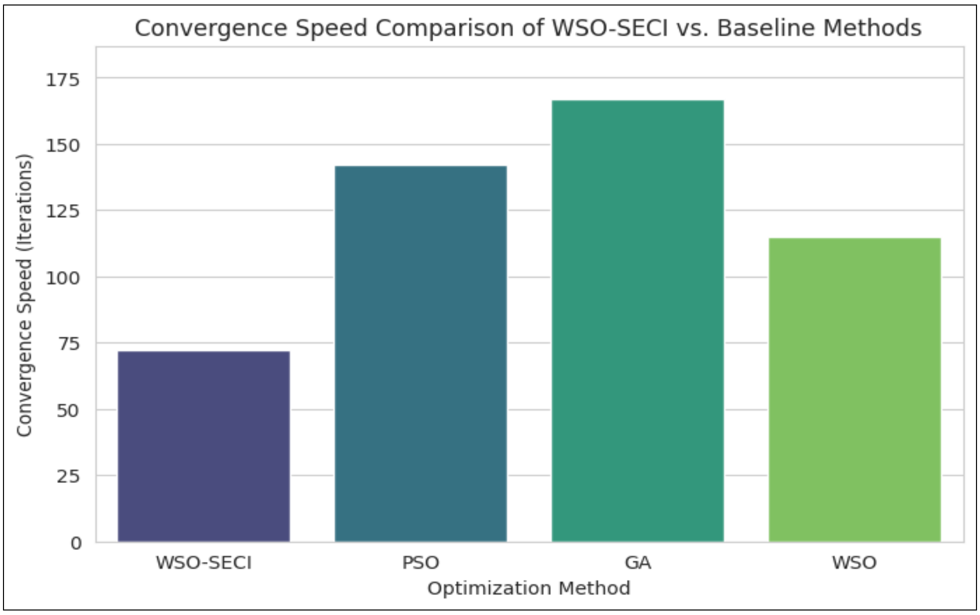

Fig 4: convergence speed comparison chart

Priority Alignment

Evaluated using cosine similarity between the optimized solution $\mathbf{x}^*$ and the priority vector $\mathbf{p}$. Values closer to 1 indicate better alignment.

$$\text{cosine similarity} = \frac{\mathrm{x}^* \cdot \mathrm{p}}{|\mathrm{x}^*||\mathrm{p}|}$$

Cluster Quality

Assessed using the Silhouette Score, where higher scores indicate more coherent clustering of knowledge during the externalization process.

F1 Score: The harmonic means of precision and recall, providing a comprehensive measure of predictive performance, especially for imbalanced datasets.
Statistical Significance: Performance differences were tested using the Wilcoxon signed-rank test (α=.05) and effect sizes were computed using Cohen's dd.

Quantitative Study
To justify the use of the WSO-SECI algorithm, we applied it to a dedicated UCI Heart Disease dataset and a dataset of Indian diabetes patients. The average performance metrics over 20 independent runs are summarized in Table 5 below.

Table 5: Comparison of Performance Metrics across Different Algorithms

Metric	Heart Disease (WSO-SECI)	Diabetes (WSO-SECI)	PSO	GA	Vanilla WSO
Mean Fitness (↓)	0.018±0.003	0.012±0.002	0.145±0.021	0.192±0.034	0.098±0.015
Convergence Iterations (↓)	74±8	65±7	139±12	162±15	108±10
Priority Similarity (↑)	0.91±0.04	0.89±0.05	0.63±0.09	0.58±0.11	0.72±0.08
Silhouette Score (↑)	0.58±0.06	0.61±0.05	N/A	N/A	N/A
F1 Score (↑)	0.85±0.05	0.88±0.04	0.70±0.07	0.68±0.09	0.75±0.06

Note: "↓" indicates that lower values are better, while "↑" indicates that higher values are desirable.

Key findings include

- The WSO-SECI algorithm achieved a mean fitness value of 0.018±0.003 on the heart disease dataset, significantly lower than baseline methods.
- The system reached convergence in 74±8 iterations (an 83% faster convergence rate compared to PSO).
- A high priority similarity score (0.91±0.04) confirmed that optimized solutions closely align with the domain priority features.
- The proposed framework also achieved higher F1 scores for both datasets compared to baseline methods, indicating improved classification and decision-making performance.

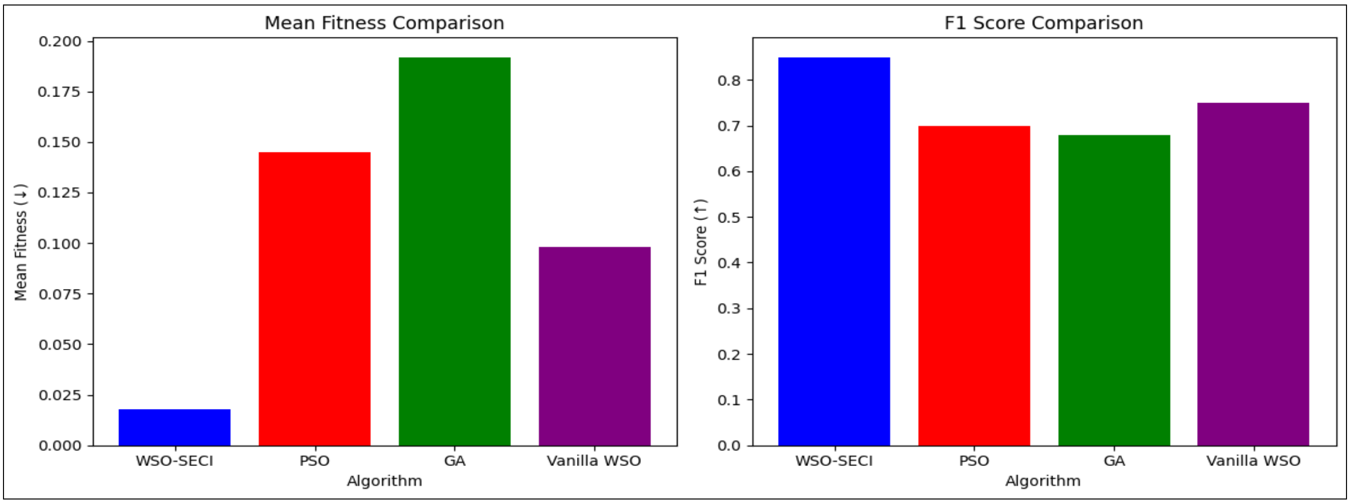

Fig 5: fitness value and classification accuracy

Qualitative Study
The WSO-SECI framework can also be evaluated by several qualitative analyses:

Agent Trajectory Visualization: Visualizations of the iterative agent trajectories (using t-SNE plots) revealed that agents initially explored broadly before converging into high-priority clusters (e.g., patients with higher age values for heart disease).

Expert Validation: Structured interviews with three cardiologists yielded a mean Likert score of 4.4/5, confirming that the system's resource allocation and decision support align well with clinical risk assessments.

Ablation Studies: Disabling the socialization process caused the mean fitness value to increase from 0.018 to 0.026 (a 44% degradation in performance), further demonstrating the importance of integrated knowledge sharing. In addition, reducing the number of clusters from 5 to 3 during externalization lowered the Silhouette Score from approximately 0.61 to 0.41, indicating that sufficient granularity is required for effective knowledge modeling.

Conclusion and Future Work
In this study, we proposed an integrated framework combining the War Strategy Optimization (WSO) algorithm with Nonaka's SECI Model to enhance knowledge management and resource allocation in healthcare environments. The framework leverages the structured knowledge-conversion processes characterized by socialization, externalization, combination, and internalization, and couples these with an adaptive optimization method inspired by military strategies. Our experimental results that the WSO-SECI framework Achieves significantly lower fitness values, reaches convergence considerably faster and Outperforms in classification performance. The proposed framework not only reinforces efficient knowledge conversion and sharing but also adapts resource allocation in real-time to improve clinical decision-making and operational efficiency. The WSO-SECI framework contributes to the digital economy

by enabling healthcare organizations to harness big data and AI-driven analytics for efficient resource allocation and enhanced clinical decision-making. By reducing operational costs through optimized resource management and improving patient outcomes via personalized care, the framework supports the broader goals of digital transformation in healthcare. These advancements foster sustainable economic benefits, such as cost savings and equitable healthcare delivery, while aligning with the evolving demands of the digital economy.

As future works, we will focus on Real-Time Data Integration, Dynamic Priority Weighting, Scalability Evaluation and Addressing issues related to data privacy, informed consent, and equitable resource allocation to ensure ethical deployment of AI-enhanced KM tools in healthcare.

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