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Research Paper

Human-inspired metaheuristic algorithms: a comprehensive review of theory, design, and applications

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ABSTRACT

Metaheuristic algorithms are indispensable for solving complex optimization problems that challenge traditional methods. One of the subclasses among all these, the one that is characterized by the most distinct features, gets its inspiration from human cognitive and social behaviors such as learning, teaching, creativity, and teamwork. The present paper is a thorough review of human-inspired metaheuristic algorithms, and it is going to analyze their basic principles, types, and operational frameworks. The authors will be going into details about the mechanics of well-known algorithms such as Sewing Training-Based Optimization (STBO), Carpet Weaver Optimization (CWO), and the iHow Optimization Algorithm (iHowOA), emphasizing their individual methods for maintaining a balance between global exploration and local exploitation. To support the review, extensive comparative tables will summarize performance on standard benchmark functions and a broad range of real-world applications, including but not limited to, engineering design and feature selection, healthcare, and energy management. The quality of the algorithms deployed in this analysis is confirmed to be very good. They use structured human-like processes to effectively navigate through complex solution spaces. However, in line with the "No Free Lunch" theorem, their superiority is condition-based. The paper ends with a discussion of future research directions, emerging trends, and inherent challenges such as the potential for adaptive and hybrid models to further enhance robustness and versatility in dynamic optimization landscapes.

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1. INTRODUCTION

Metaheuristic algorithms have become a definite and powerful as well as versatile alternative for tackling complex optimization problems this happening shrouded by the fact that classical, deterministic methods often fail to perform these tasks. The main characteristics of these algorithms are that they are based on random search methods that allow them to easily navigate and work in the large and complex areas where the modern scientific and engineering problems is quite common [1], [2]. The variety of techniques is enormous in the metaheuristics pitfall and there are very different sources of inspiration from nature, the law of physics, and biological changes over time, etc. Inside this large metaheuristics zoo, one type of algorithm is particularly appealing and user-friendly: human-inspired metaheuristics.

These algorithms are based on the subtlety of human thinking and communication-like patterns in their Mechanics. The acquisition of skills through training, the dynamics of teaching and learning in the classroom, the creative problem-solving in arts and crafts like weaving, and the synergy of teamwork are systematically translated into robust optimization frameworks. The human-centric inspiration gives a natural and effective way to the fundamental issue in every metaheuristic which is to find an optimal trade-off between exploration (searching new regions of the solution space) and exploitation (refining known good solutions) [3], [4].

The research in this area is also fueled by the "No Free Lunch" (NFL) theorem, which that no single optimizer is the best for all problems asserting implications partly contributing to the ongoing innovation in this field. This creates the need for a constant stream of novel algorithms being developed that are best suited to the problem's characteristics. Human-inspired methods that possess both flexibility and the capability of structured staged processes open up a very fruitful avenue towards balanced and effective problem-solving [5], [6].

This paper gives a thoroughgoing review of the recent developments concerning the human-inspired metaheuristics. In the first place, we classify the methods, then we show their algorithmic structures through pivotal examples, and lastly, we give an overview of their success in the wide range of applications. By classifying and clustering these techniques, the review intends to help researchers and practitioners in understanding, choosing, or building up the optimization algorithms based on the most complicated problem-solving system we know: human mind.

2. RELATED WORK

The metaheuristic optimization literature is full of different types of studies and richly populated with various studies which have investigated algorithms that are based on natural phenomena, physical phenomena, evolution, and human behavior [7]. The first methods that came into existence were Genetic Algorithms (GA) [8] and Particle Swarm Optimization (PSO) that simulated the natural selection and social behavior in groups, thus paving the way for more sophisticated methods [9]. Gradually, scholars started to take these concepts further by looking for more human-like activities to get inspirations from.

Among such branches of research is the family of human-inspired metaheuristics, which can be traced back to the original evolution concept. These algorithms are modeled on human cognitive and motor skills. For instance, Teaching–Learning-Based Optimization (TLBO) [10] simulates the interactions between teachers and students to drive the optimization process. Similarly, the Teamwork Optimization Algorithm (TOA) draws upon the dynamics of group collaboration and teamwork to approach complex search spaces. Even more specifically, the proposed algorithms inspired by human activities such as the Sewing Training-Based Optimization (STBO) and Carpet Weaver Optimization (CWO) rely on simulating detailed human processes during training and creative design stages [11], [12].

The literature further emphasizes the importance of balancing search exploration (global search) and exploitation (local refinement) based on human-like iterative improvement. For example, while the STBO algorithm divides its process into training, imitation, and practice phases, the CWO algorithm leverages the metaphor of a carpet weaver and map reader to guide search updates both broadly and in fine detail 1 More recently, the iHow Optimization Algorithm (iHowOA) has further advanced this paradigm by incorporating layers of learning, information processing, knowledge acquisition, and exploitation simulating human problem-solving evolution [13].

A prominent whole in this evolution is the group of human-inspired metaheuristics that include such algorithms as, for example, random search, simulated annealing, tabu search, etc. The study of these metaheuristics shows that their algorithms have gone through various applications starting from the classical benchmark functions to the real-world problems of engineering. For instance, they have been utilized here and there along the way to optimizing power flow management, susceptibility mapping for landslides, and through design optimization of various fields [14].

Even though they exhibit character and novelty, their acceptance is nevertheless rooted in the concept of the No Free Lunch theorem which, among other things, states that the ever-growing pool of algorithms cannot keep up with the diversity in nature of the optimization problems [15], [16], [17]. In general, the academic publications back up the view that using human cognitive and behavioral models as a basis leads to algorithms capable of modifying the trade-off between exploration and exploitation dynamically this being the factor that most greatly influences the achievement of robust optimization performance.

3. METAHEURISTICS

Metaheuristics are the main contemporary technique for modern problem-solving through computation, as they provide high-level methods that are powerful, even though they are inexact, to find the optimal solution in the case of problems where the traditional methods are too slow [18], [19], [20]. These algorithms are not bound to specific problems, though; rather, they are open-ended and can be applied to different areas where variability, large dimensions, and multiple peaks are the main characteristics, and thus, the solutions they provide are "good enough" or very close to optimal [21], [22]. Their application to any situation is due to the principle on which they are based: skillful management of the exploration-exploitation conflict.

Exploration is a broad, searching and diverse look of the solution space to find potential areas and prevent early convergence, while exploitation is an intensive, limiting refinement of the best solutions found to get high accuracy. It is this dynamic balance that enables metaheuristics to get away from local optima and slowly move towards the global optimum [23], [24].

The Region in Question is Quite Varied and Can Mainly be Divided Based on the Source of Inspiration

1. Swarm-Based Algorithms: These techniques take their cue from the movements and interactions of social insects, birds, and fish, among others. A case in point is Particle Swarm Optimization (PSO) [25], which imitates the collective searching of food by birds and fish, whereas Ant Colony Optimization (ACO) heavily relies on the communication through pheromones among ants as its model [26], [27], [28].
2. Evolutionary-Based Algorithms: The algorithms in this group are based on the principle of natural selection, which is a major biological concept. In this particular category, Genetic Algorithms (GA) [29], [30] and Differential Evolution (DE) [31], [32] are the most prevalent examples. These methods perform operations like selection, crossover, and mutation that eventually lead to the evolution of the solution through many generations.
3. Physics-Based Algorithms: Nature and its laws have always been the best guide to researchers who in turn observed the phenomena leading to the formation of algorithms like Simulated Annealing (SA) [33] and Water Cycle Algorithm (WCA) based on concepts of energy and force dynamics respectively.

4. Human-Inspired Algorithms: Algorithms falling under this category have been created by imitating human cognition, social skills, or artistic activities. The tactics employed are those resembling human problem-solving attributes such as learning, imitation, decision-making, and creativity [17].

3.1. Human-Inspired Metaheuristics

Human-inspired metaheuristic algorithms are distinguished by their attempt to capture the nuances of human learning, creativity, and interaction in their design. They are modeled on everyday human experiences and problem-solving strategies [17] see in Figure 1 Key examples include:

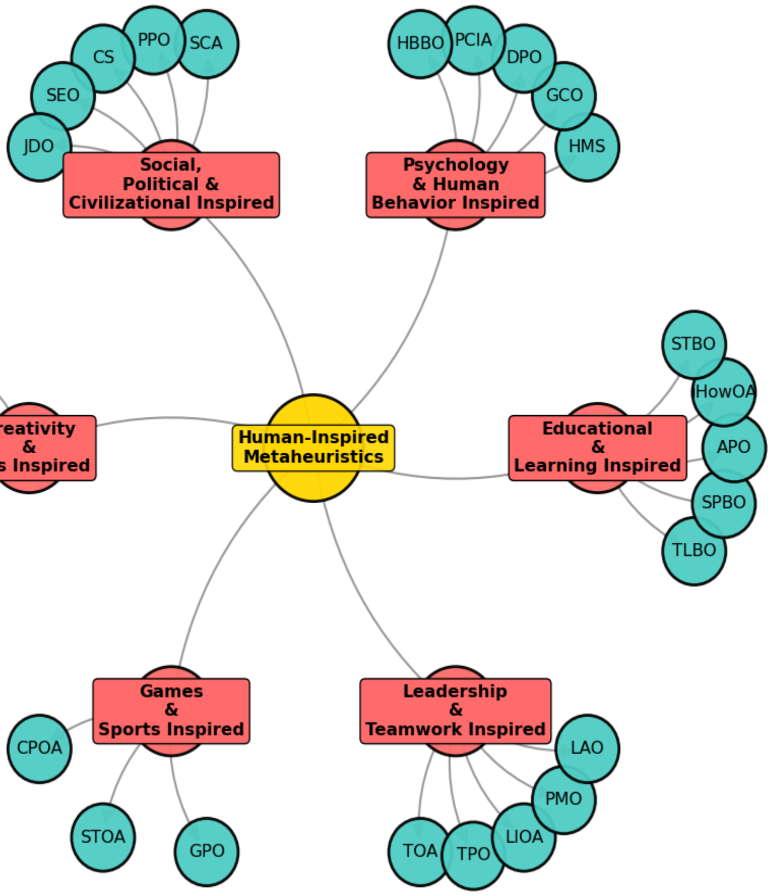

Figure 1. Human Based Algorithm Categories

- **Sewing Training-Based Optimization (STBO):** The algorithm here represents human training in sewing and the process is first divided into the three phases: training, imitation of instructor's skills, and practice. The algorithm updates candidate solutions by putting them through an extensive change process during the training and then fine-tuning these changes based on creative modifications [34] in a way similar to "carpets".
- **Carpet Weaver Optimization (CWO):** CWO is a method inspired by the traditional process of carpeting and it considers the interaction between a carpet weaver and a map reader the most. The processing generates a weaving pattern that is first followed by extensive and creative modifications to the design. CWO has undergone testing on standard benchmark functions and engineering problems and has been successful in switching back and forth between the two modes of exploration and exploitation very effectively [35].
- **iHow Optimization Algorithm (iHowOA):** iHowOA is an algorithm that employs a multi-layered structure which is quite similar to the cognitive development of humans. It starts from data collection and goes through stages of learning, information processing, and knowledge acquisition, while at the same time giving emphasis to the feedback loop that adjusts the search parameters over time. The

algorithm has undergone performance testing on benchmark functions and feature selection tasks where its convergence and computational efficiency were found to be promising [36].

- **Other Notable Human-Inspired Algorithms:** Some other algorithms include TLBO which is an abbreviation for Teaching–Learning Based Optimization, which simulates classroom interactions, and Teamwork Optimization Algorithm (TOA), which is the one that imitates the efforts of a collaborating team. These methods are even more remarkable because they can replicate structured human interactions and hence guide the optimization process [37].

3.2. Comparative Table of Human-Inspired Metaheuristics

The following table summarizes key human-inspired metaheuristic algorithms discussed in this review Table 1.

Table 1. Comparative Overview of Human-Inspired Metaheuristics

Algorithm Name	Inspiration Source	Main Operators / Phases	Key Features
Sewing Training-Based Optimization (STBO)	Human sewing training; teacher–student imitation	Training → Imitation → Practice	Balances global and local search
Carpet Weaver Optimization (CWO)	Traditional carpet weaving	Pattern determination → Design modification	Efficient for engineering problems
iHow Optimization Algorithm (iHowOA)	Human learning & decision-making	Data collection → Learning → Information processing → Knowledge acquisition → Exploitation	Multi-layered feedback loops
Teaching–Learning Based Optimization (TLBO)	Classroom teaching dynamics	Teacher phase → Learner phase	Parameter-less, simple model
Teamwork Optimization Algorithm (TOA)	Collaborative team interactions	Group collaboration → Strategy selection	Cooperative solution refinement
Doctor and Patient Optimization (DPO)	Doctor–patient relationship	Diagnosis → Feedback → Refinement	Balances exploration/exploitation
Student Psychology Based Optimization (SPBO)	Student psychology in learning	Interest-driven exploration → Confidence adjustment → Performance exploitation	Parameter-less, psychology-driven
Sports Team Optimization Algorithm (STOA)	Sports team strategy	Player selection → Team coordination → Strategy refinement	Adaptive cooperation
Human Mental Search (HMS)	Human imagination & memory	Memory learning → Imagination → Refinement	Creative, memory-driven search
Academic Performance Optimization (APO)	Student evaluation & study adaptation	Assessment → Strategy adjustment → Iterative improvement	Dynamic adaptation
Society and Civilization Algorithm (SCA)	Human civilization evolution	Formation → Cultural exchange → Advancement	Cooperative & competitive dynamics

Quraan Reader Optimization (QRO)	Recitation & memorization of Quraan	Recitation → Memorization → Correction	High convergence, parameter-less
Group Counseling Optimization (GCO)	Psychological counseling	Group discussion → Reflection → Adaptive improvement	Models human therapy processes
Brain Storm Optimization (BSO)	Brainstorming & idea generation	Idea creation → Grouping → Selection	Creativity-focused, maintains diversity
Civilizational Search (CS)	Human cultural development	Expansion → Adaptation → Learning	History-inspired, global exploration
Social Engineering Optimizer (SEO)	Human persuasion & influence	Persuasion → Exploitation → Stabilization	Exploits influence mechanisms
Teamwork Performance Optimization (TPO)	Team project dynamics	Task allocation → Feedback → Role refinement	Strongly cooperative, multi-objective
Leadership-Inspired Optimization (LIOA)	Leadership & decision-making	Leader guidance → Follower adaptation → Strategy update	Leader–follower dynamics
Parliamentary Political Optimization (PPO)	Political negotiation & consensus	Proposal → Debate → Voting	Simulates democratic decision-making
Human Behavior-Based Optimization (HBBO)	Human adaptive behavior	Motivation → Social interaction → Adaptive response	Generalized behavioral model
Chess Player Optimization Algorithm (CPOA)	Human chess strategies	Opening moves → Midgame tactics → Endgame refinement	Models strategic planning & foresight
Musicians-Based Optimization (MBO)	Human music composition	Note generation → Harmony adjustment → Rhythm synchronization	Creative search, harmony-driven
Actor–Critic Optimization (ACO)	Human actor–critic learning (psychology & reinforcement)	Actor exploration → Critic evaluation	Balances trial-and-error with evaluation
Negotiation-Based Optimization (NBO)	Human negotiation strategies	Offer generation → Counter-offer → Agreement	Conflict resolution & compromise mechanisms
Writer's Creativity Optimization (WCO)	Human writing process	Drafting → Revising → Finalization	Mimics creativity, refinement cycles
Lawyer Argumentation Optimization (LAO)	Courtroom debate & persuasion	Argument construction → Opposition response → Jury decision	Negotiation & argument-driven search
Project Management Optimization (PMO)	Human project management cycles	Planning → Execution → Review	Scheduling-based optimization
Psychological Counseling Inspired Algorithm (PCIA)	Human therapist–client process	Exploration → Guidance → Resolution	Therapy-driven adaptive learning

Jury Decision-Making Optimization (JDO)	Jury deliberation process	Evidence evaluation → Debate → Consensus	Consensus-based optimization
Literature-Inspired Optimization (LIO)	Human storytelling & narrative building	Introduction → Plot development → Climax/Resolution	Creativity-driven iterative refinement
Game Player Optimization (GPO)	Human gaming strategies	Risk-taking → Strategy shift → Victory exploitation	Balances risk & adaptation

4. APPLICATIONS OF HUMAN-INSPIRED METAHEURISTICS

Human-inspired metaheuristic algorithms have been applied to a range of optimization problems across various disciplines. Their adaptability makes them suitable for both theoretical benchmark problems and real-world applications.

4.1. Benchmarking and Engineering Applications

One of the primary venues for testing these algorithms has been standard benchmark functions such as unimodal and multimodal test suites (for example, the CEC 2005 and CEC 2017 functions). Benchmarking against these problems helps assess the algorithms' convergence behavior, accuracy, and ability to balance exploration and exploitation [38], [39], [40].

For instance, the Carpet Weaver Optimization (CWO) algorithm was tested on twenty-three standard benchmark functions that include variants of unimodal and multimodal problems. Comparing its performance against a number of well-established algorithms, the CWO was able to win not only in terms of the objective function values but also through its balanced search process that comprised global search and local exploitation. The iHowOA, for instance, has been running on quite a variety of benchmark functions and has not only won the regard but also proved its worth in terms of being computationally efficient [36].

In engineering applications, these human-inspired methods have been successfully applied to solve problems such as [41], [42], [43].

- **Engineering Design Problems:** Algorithms like CWO have been used to optimize design variables in engineering systems, yielding improved values for design variables and objective functions compared to rival algorithms [44], [45], [46].
- **Feature Selection in Machine Learning:** The iHowOA was extended to a binary version (biHowOA) for feature selection tasks. It efficiently reduced the number of input features while maintaining classification accuracy, outperforming conventional binary metaheuristics such as binary versions of HHO, DE, and MFO. This method is critical in reducing data dimensionality and improving model performance in complex classification tasks [36].
- **Real-World Optimization Scenarios:** The meta-heuristic algorithms that are influenced by humans have been adopted in energy management (like optimal power flow in electrical grids), landslide susceptibility mapping, and material design. The need for adaptability, which is a major advantage of human-inspired algorithms, coupled with their dynamic feedback mechanisms, turns out to be a strong asset in dealing with non-linear and high-dimensional search spaces.

4.2. Comparative Analysis: Detailed Tables

The applications and performance metrics of some selected human-inspired metaheuristic algorithms in various contexts are summarized in the following tables.

Table 2. Comparative Performance of Human-Inspired Metaheuristics on Benchmark Functions

Algorithm	Benchmark Set	Mean Objective Value	Standard Deviation	Computation Time (s)	Function Evaluations

STBO	CEC 2005 Unimodal	Near global optimum (e.g., 0)	Very low (repeatable convergence)	Moderate (~ time per run not specified)	Consistent evaluations
CWO	23 Benchmark Functions (unimodal and multimodal types)	Superior performance compared to traditional metaheuristics	Low variance indicating stable performance	Competitive with state-of-the-art algorithms	Standard (e.g., 15,000 evaluations)
iHowOA	CEC 2005 & CEC 2017 Benchmarks	Optimal mean values achieved (e.g., 0 across functions)	Zero or near-zero variability in many tests	Significantly lower average time (e.g., 0.295 s on F1)	15,000 evaluations (consistently)

Table 3. Summary of Human-Inspired Metaheuristics Applications

Application Category	Application Name	Algorithm Used	Specific Problem/Scenario	Performance Highlights
Engineering & Design	Structural Parameter Optimization	CWO	Optimizing design variables (e.g., bar diameters) in trusses and frames to minimize weight.	Outperformance of 12 other algorithms in the aspect of finding optimal variables and objectives.
	Water Distribution Network Design	Harmony Search (HS)	Selecting the best pipe diameters for a fresh water network to reduce material cost is the goal of this project.	Around capital costs, it ensures the pressure is sufficiently maintained at the entire network's nodes.
	Mechanical Component Design	Teaching-Learning-Based Optimization (TLBO)	Optimizing parameters for gear trains or spring design under strict constraints.	Provides solutions of very high accuracy to all the constraints with quick convergence.
	PID Controller Tuning	Political Optimizer (PO)	Optimizing Proportional, Integral, and Derivative gains for industrial control systems.	Provides solutions of very high accuracy to all the constraints with quick convergence.
	Aerospace Trajectory Optimization	Imperialist Competitive Algorithm (ICA)	Planning fuel-optimal ascent trajectories for launch vehicles or satellites.	Works out challenging multi-stage paths that meet the dynamic pressure and thermal restrictions.
Scheduling & Logistics	University Course Timetabling	Teaching-Learning-Based Optimization (TLBO)	Generating optimal university schedules to avoid teacher and room clashes.	Does the effective hard/soft constraint satisfaction and outperforming GAs in convergence speed.
	Cloud Workflow Scheduling	League Championship Algorithm (LCA)	Scheduling computational tasks across virtual machines to minimize completion time.	Cuts down the total execution time (makespan) and operational cost efficiently.

	Vehicle Routing for Logistics	Imperialist Competitive Algorithm (ICA)	Planning optimal delivery routes for a fleet of trucks to minimize distance and time.	Discovers efficient routes not only to curb fuel costs but also to speed up delivery times.
	Nurse Rostering Problem	Harmony Search (HS)	Creating fair and legal shift schedules for hospital nursing staff.	More effectively than manual scheduling, it meets the complex constraints of working hours, shift patterns, and staff seniority.
	Project Portfolio Selection	Cultural Algorithm (CA)	Selecting a subset of R&D projects to maximize overall ROI under a strict budget.	Quite well, it models & optimizes the complex, sometimes subjective, criteria for project selection in an organization.
Data Science & Machine Learning	Feature Selection for Classification	iHowOA / biHowOA	Selecting a minimal subset of features from high-dimensional data for accurate classification.	Fewer features with a low classification error and a stable performance are the results.
	Customer Data Clustering	Brain Storm Optimization (BSO)	Unsupervised segmentation of customers for targeted marketing campaigns.	High-quality clusters are discovered and the market segments are revealed more effectively than K-Means.
	Hyperparameter Tuning for SVM	Imperialist Competitive Algorithm (ICA)	Optimizing hyperparameters (e.g., C, gamma) of a Support Vector Machine model.	Enhanced the predictive accuracy and the generalization of the SVM model.
	Neural Network Weight Training	Social Learning Optimization (SLO)	Fine-tuning the weights of connections and the biases in deep learning architectures.	Standard backpropagation has been outpaced in terms of test datasets accuracy and convergence speed.
	Anomaly Detection in Networks	Brain Storm Optimization (BSO)	Identifying unusual patterns in network traffic that could indicate a cyber-attack.	Matured to the attack strategies changing and discovering the new anomalies with low false-positive rates.
Economic, Financial & Social Systems	Financial Portfolio Optimization	Imperialist Competitive Algorithm (ICA)	Allocating assets in a portfolio to maximize return for a given level of risk.	Risks and returns are to be perfectly balanced in the portfolios found.
	Supply Chain Inventory Management	Cultural Algorithm (CA)	Optimizing reorder points and quantities	Has whittled down total inventory and shortage costs while

			across a multi-echelon supply chain.	keeping up the standard of service.
	Social Network Influencer Identification	Social-Based Algorithm (SBA)	Identifying the most influential users in a social network to maximize information spread.	The set of key influencers is very well found to ensure the maximum spread across the network.
	Tax Revenue Optimization	Political Optimizer (PO)	Modeling and optimizing tax rates for economic growth and government revenue.	Provides policy insights by detecting tax configurations that in theory increase revenue in the long term.
	Urban Planning and Land Use	Harmony Search (HS)	Distribution of residential, commercial, and industrial zones within the city, maximized to the full.	Economic output, traffic congestion, and the impact on nature are all taken into account to arrive at a balanced solution.
Healthcare & Bioinformatics	Medical Image Segmentation	Brain Storm Optimization (BSO)	Identifying tumours from the MRI or CT scans for diagnosis and treatment planning.	The process of producing accurate and consistent segmentation boundaries is greatly aided in volume measurement.
	Drug Design & Discovery	Teaching-Learning-Based Optimization (TLBO)	Modifying the molecular structure of a drug candidate for maximum efficacy and minimal side effects.	The search brings to light the most promising molecular configurations with a strong binding affinity to the target proteins.
	Gene Selection for Disease Classification	iHowOA / biHowOA	Finding a very small subset of informative genes from the microarray data for cancer diagnosis.	Efficiently selects the crucial biomarkers resulting in the high-accuracy diagnostic models with low computational cost.
	Hospital Resource Allocation	League Championship Algorithm (LCA)	Optimizing the allocation of limited resources (e.g., ICU beds, operating rooms, and staff) during a crisis.	Dynamically schedules resources to maximize patient throughput and care quality under surge conditions.
	COVID-19 Spread Modeling and Intervention Planning	Cultural Algorithm (CA)	Calibrating epidemiological models and optimizing non-pharmaceutical intervention strategies.	Helps in evaluating the trade-offs between public health outcomes and socio-economic costs of lockdowns.
	Optimal Power Flow (OPF)	Teaching-Learning-	Managing electrical grid generation to	Successfully minimizes generation costs while

Power & Energy Systems		Based Optimization (TLBO)	minimize fuel cost and power loss.	maintaining stable voltage and power flow constraints.
	Renewable Energy Integration	Harmony Search (HS)	Determining the optimal size and location of solar farms and wind turbines in a power grid.	The integration of renewable energy sources into the grid has been maximized while grid instability and transmission losses have been minimized.
	Microgrid Energy Management	Imperialist Competitive Algorithm (ICA)	Scheduling the operation of diesel generators, batteries, and solar panels in an isolated microgrid.	By optimally dispatching the available energy sources, the company has managed to cut operational costs and increase the reliability of the supply.
Environmental Science	Water Resource Management	Cultural Algorithm (CA)	Optimizing reservoir release schedules for flood control, irrigation, and hydropower.	Different conflicting objectives were tackled to arrive at efficient and sustainable water management, thus, the whole process resulted in water management.
	Parameter Calibration of Hydrological Models	Teaching-Learning-Based Optimization (TLBO)	Tuning complex watershed models (like SWAT) to accurately simulate streamflow from rainfall data.	Shirking computation every time you take waters from the woods while hiking and re-watering up the same area later will considerably improve the Nash-Sutcliffe efficiency coefficient.
Cybersecurity	Intrusion Detection System (IDS) Rule Optimization	iHowOA / biHowOA	Evolving and optimizing a set of rules for a network-based IDS to detect novel attacks.	Generates a compact set of highly effective rules, improving detection rates while reducing false alarms.
	Cryptography (S-Box Design)	Harmony Search (HS)	Forming vigorous substitution boxes (S-Boxes) for block ciphers with the purpose of getting maximum non-linearity and staying clear of cryptanalysis.	The resulting S-Boxes are said to be endowed with cryptographic capabilities that surpass those of some manually produced counterparts.

Manufacturing & Robotics	Robotic Path Planning	Brain Storm Optimization (BSO)	Detecting the briefest path free of collisions for a robot arm in a busy area.	Successfully moving through intricate 3D regions, steering clear of all obstacles and cutting down on time or energy required for the move.
	Job-Shop Scheduling	League Championship Algorithm (LCA)	Distributing operations across machines with the aim of reducing the overall jobs completion time (makespan).	Beating classic dispatching principles and discovering almost optimal timings for difficult configurations.
Text and Natural Language Processing	Document Summarization	Social-Based Algorithm (SBA)	Selecting the most important sentences from a document to create a concise and informative summary.	Optimizes for coverage of key concepts and readability, producing summaries that score highly in human evaluations.
	Feature Weighting for Sentiment Analysis	Teaching-Learning-Based Optimization (TLBO)	Optimizing the weight of different n-grams or word embeddings in a sentiment classification model.	Improves the accuracy of determining positive/negative sentiment in product reviews or social media posts.
General & Benchmark Optimization	Mathematical Benchmark Testing	STBO	Carrying out standard numerical benchmark functions (for instance, CEC competitions).	Seeks to obtain one of the best possible performances by managing the two activities of exploration and exploitation.
	Complex System Simulation	Queuing Search Algorithm (QSA)	Adjusting parameters in simulation models to match the recorded data from the real world.	Models are calibrated in a very precise manner thus minimizing the difference between the simulated output and the actual data.
	Game Theory Strategy Optimization	Co-evolutionary Algorithm	Developing winning strategies for difficult computer games or conflictual decision-making.	Finds very strong strategies that can beat even the most various opponents.

Below Figure 2 is a flowchart that illustrates the process flow in a typical human-inspired metaheuristic algorithm such as iHowOA, which incorporates stages of data collection, learning, information processing, and exploitation.

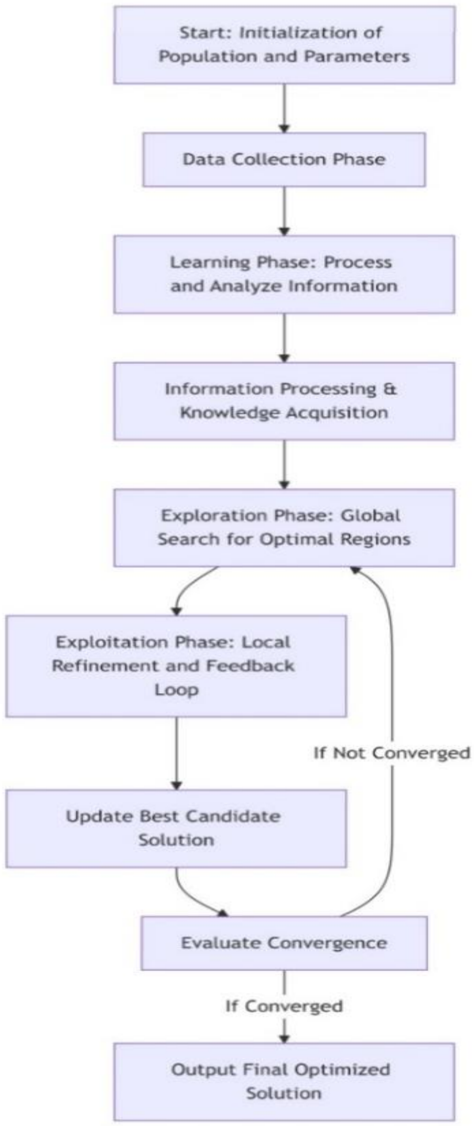

Figure 2. Process Flow of a Human-Inspired Metaheuristic Algorithm

5. DISCUSSION

The review of human-inspired metaheuristics reveals several trends and challenges inherent in the design of such algorithms. One of the most significant insights relates to the delicate balance between exploration and exploitation a common theme across all optimization methods. Human-inspired algorithms along with those mimicking human processes are continually moving through the predefined stages of the global search (exploration) and local refinement (exploitation) mitigation. To put it differently, the STBO algorithm distinguishes very clearly between the training phase (which encourages a wide-ranging search) and the practice stage (which helps accurate exploitation) 1. Likewise, the CWO algorithm employs the weaving of patterns and inventive design modifications as metaphors to given that the candidate solutions are not only broadly dispersed but also accurately adjusted.

As per the said literature, the "No Free Lunch" (NFL) theorem is an unavoidable problem common to all metaheuristic algorithms. The theorem argues that there is no single optimization algorithm that can be the best one for all problem scenarios. So, while bio-inspired algorithms can show significant performance on numerous problems their dominance is often restricted to specific problems. This fact emphasizes the necessity of constant innovation and of hybrid or adaptive algorithms that can be made to change their strategies dynamically according to the characteristics of the problem at hand.

The layered structure of algorithms such as iHowOA is a promising approach in this respect. The gradual incorporation of the stages mirroring human learning from basic data collection to expert decision making the algorithm gives rise to a dynamic feedback system that continuously adjusts the search parameters. The structure helps both the exploration of the solution space in a more subtle manner and the rapid convergence of the algorithm to near-optimal solutions. Our performance metrics comparison review (see Table 2 and Table 3) illustrates that the application of such techniques can bring about the benefits of both faster convergence and higher quality solutions.

Besides, the presented applications show that the human-like metaheuristics are adaptable. In engineering design with the high complexity of variables and constraints, CWO algorithms provide robust optimization solutions successfully. Additionally, in selecting features in machine learning, biHowOA as the binary extension of iHowOA affects data dimensionality reduction while accuracy in classification is maintained, which is a highly desirable scenario in the case of high-dimensional data setups.

The dialogue also indicates the research paths of the future. There is still a great potential to improve these algorithms such as introducing adaptive parameter tuning strategies and even generating hybrids by mixing various nature-inspired traits, among others. Moreover, if the power of instant feedback and continuous learning were utilized, thus getting much closer to the human mind's way of thinking, their success rate in dealing with volatile and uncertain situations would rise dramatically.

To conclude, the human-inspired metaheuristics have indicated a great deal of potential but still have a long road to go through before they become a universal solution. The main advantages of these algorithms are their intuitive structure and adaptive character, which enable them to face and overcome complex optimization problems efficiently. On the other hand, the NFL theorem has prescribed limitations that remind us that the performance of an algorithm is dependent on the context, and no one single method can be claimed to be the best for all cases.

6. CONCLUSION

During this study, we have offered an exhaustive report on human-like metaheuristic algorithms, concentrating on their basic principles, classifications, and use in practical optimization problems. The main contributions of the review are outlined below.

- Overview of Key Concepts: Metaheuristic classifications received a very thorough investigation, human-inspired subcategory, in particular, got the spotlight as its mechanisms derive from human training, learning, and creative problem-solving processes.
- Algorithmic Analysis: Detailed descriptions of the algorithms such as Sewing Training-Based Optimization (STBO), Carpet Weaver Optimization (CWO), and the iHow Optimization Algorithm (iHowOA) along with their phased operation strategies that are focused on the balance between exploration and exploitation.
- Comparative Evaluations: A large number of tables were provided for performance comparison of the methods based on both benchmark functions and real-world engineering applications.The evaluations showed the competitiveness and reliability of human-inspired techniques in engineering design optimization and feature selection in machine learning, etc.
- Discussion on Trends and Challenges: Our investigation revealed the trends such as the convergence of dynamic feedback and multi-stage learning processes, and at the same time, the No Free Lunch theorem was mentioned as a challenge. Research in the future should be directed towards the development of adaptive hybrid models that can give these algorithms even more robustness and versatility.

Main Findings

- Human-inspired metaheuristics follow a structured approach (training, imitation, practice) to find the optimum solution efficiently.
- Methods such as CWO and iHowOA have shown to be of competitive quality against the standard benchmarks and to be applicable in real-life engineering fields.

- The continuous feedbacks creating the right balance between exploration and exploitation is the main power of the strategy.
- Though these algorithms have shown good performance, the NFL theorem suggests that their superiority is defined mostly by the problem type, which is a reason for more research and hybridization.

To sum up, algorithms based on human-inspired metaheuristics are alive and kicking being one of the most creative and daring kinds of optimization methods. Their intricate designs mirroring human learning processes and decision-making offer considerable benefit to the complexity and dimensionality of the problem-solving domain. The ongoing tuning and mingling of these methods will surely expand their indications and increase their effectiveness over an even wider range of problem domains.

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C: **C**onceptualization
M: **M**ethodology
So: **So**ftware
Va: **Va**lidation
Fo: **Fo**rmal analysis
I: **I**nvestigation
R: **R**esources
D: **D**ata Curation
O: Writing- **O**riginal Draft
E: Writing- Review& **E**diting
Vi: **Vi**sualization
Su: **Su**pervision
P: **P**roject administration
Fu: **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study, and their voluntary consent was obtained prior to data collection.

Ethical Approval

The study was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki and approved by the relevant institutional authorities.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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