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A Systematic Review of Metaheuristic-Metaheuristic (MH-MH) Hybridizations for Optimization

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Abstract: This systematic review following the PRISMA framework analyzes metaheuristic-metaheuristic (MH-MH) hybridizations published between January and October 2024 to uncover patterns of algorithmic dominance, functional roles and integration strategies, metaphor-based partnerships, domain mappings and evaluation orientations. Frequency mapping of 105 canonical algorithms identified Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) as the three most recurrent MHs, appearing in 20 (19.2%), 14 (13.5%), and 9 (8.7%) studies, respectively. Functional and structural analysis focused on PSO as the leading applied MH revealed its dual role as a global exploration driver and local exploitation engine, supported by balanced adoption of cooperative (45%) and sequential (45%) integration strategies. In comparison, embedded configurations accounted for the remaining 10%. Metaphor-based partner classification of the three most frequently applied canonical MHs showed that most hybrids combined flying and terrestrial swarm algorithms. Evaluation orientation analysis of the three most applied MHs indicated a gradual shift from benchmark-based validation toward domain-driven assessment, particularly in energy systems (30%), biomedical and health analytics (20%), and networking applications (15%). The review demonstrates that MH-MH hybrid success in 2024 is shaped by three interdependent design principles: Algorithmic complementarity that ensures exploration-exploitation balance, metaphorical congruence that sustains behavioral coherence, and evaluation coherence that aligns methodological rigor with domain relevance. These findings establish a unified empirical and theoretical foundation for the development of interpretable, adaptive, and reproducible hybrids.

Keywords: Metaheuristics, Hybrids, Optimization, Systematic Review, Particle Swarm Optimization

Introduction

Metaheuristic (MH) algorithms have become essential for addressing large-scale, nonlinear, and multimodal optimization problems that defy analytical or gradient-based methods. These algorithms use stochastic search mechanisms to balance exploration (global diversification) and exploitation (local intensification) to locate near-optimal solutions within complex continuous, discrete, or mixed-variable spaces (Agor et al., 2024a). Recent contributions (Agor et al., 2024b-c) have further illustrated the versatility of MH design. Over the past two decades, the field has progressed from single-algorithm models to deliberately engineered Hybrid Metaheuristics (HMs) designed to exploit complementary strengths among algorithms while mitigating individual weaknesses such as premature convergence and parameter sensitivity. A recent contribution by Agor et al. (2025) exemplifies this evolution through a hybrid of Intelligent Water Drops and River Formation Dynamics designed for optimal routing and energy-efficient path selection in MANETs.

Hybridization represents the systematic combination of algorithmic components to achieve synergy in solving complex optimization problems (Blum and Raidl, 2016). It must be deliberate, coordinating exploration and exploitation under explicit design control rather than through arbitrary aggregation (Dey et al., 2018). HMs, also known as MH hybrids, are integrative frameworks where distinct search algorithms cooperate through structured interaction, information exchange, and behavioral complementarity to enhance convergence efficiency (Hassan and Pillay, 2019; Raidl, 2006). When hybridization involves MHs combined exclusively with other MHs, the resulting framework is termed a metaheuristic-metaheuristic (MH-MH) hybrid. An MH-MH hybrid therefore constitutes a structured paradigm in which metaheuristic processes operate collaboratively or sequentially to improve solution quality, balance exploration and exploitation, and ensure robustness across optimization contexts.

The architecture of MH-MH hybrids typically follows three structural forms: cooperative, sequential, and embedded integration (Blum and Raidl, 2016). Cooperative designs allow parallel or shared information exchange among algorithms; sequential hybrids operate as multi-phase pipelines in which one algorithm initializes or refines another; and embedded hybrids integrate an operator or functional component of one algorithm into another's update mechanism. These integration structures determine how functional roles such as exploration and exploitation are distributed, establishing the basis for systematic mapping of hybrid behaviors.

A crucial theoretical dimension of MH-MH hybrids lies in metaphor-based classification, which identifies the algorithmic families from which hybrid partners are drawn. Recent taxonomic work by Agor et al. (2024a) categorizes MHs into six major families: Human, sports, music, physics-chemistry, math, and bio MHs. Each family encapsulates a distinct behavioral metaphor that models adaptive processes in real or abstract systems. For instance, bio MHs encompass plant, evolution, and swarm intelligence subgroups, with swarm intelligence methods further divided into aquatic, flying, terrestrial, and micro-organisms subtypes (Agor et al., 2025). These metaphors are not merely symbolic; as Ting et al. (2015); Raidl et al. (2019) argued, behavioral congruence between algorithmic metaphors directly affects integration feasibility and synchronization of control dynamics, making metaphor compatibility a theoretical determinant of hybrid stability.

Despite these conceptual foundations, research on MH-MH hybrids remains fragmented and often limited to performance-oriented reporting. Earlier reviews have documented broad application trends (Azevedo et al., 2024; Silva Junior et al., 2024; Naghavipour et al., 2022), yet few have examined how canonical algorithms function within hybrid frameworks or how their roles as exploration or exploitation drivers are structurally assigned. In this study, canonical MHs refer to well-established foundational algorithms that serve as the core search frameworks for hybridization. These include Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Genetic Algorithm (GA), and related models that demonstrate consistent adaptability and reproducibility across diverse optimization domains. Additionally, inconsistencies in metaphor alignment and evaluation protocols hinder cumulative understanding and reproducibility. Theoretical contributions by Blum and Raidl (2016); Dey et al. (2018) have called for systematic analysis that links algorithmic function, structural integration, and evaluative context, an imperative this review addresses through a focused examination of MH-MH hybridization patterns.

Grounded in these theoretical and methodological frameworks, the present review performs a structured synthesis of MH-MH hybrids, employing the PRISMA protocol for transparency and reproducibility. By analyzing algorithmic frequency distributions, functional roles and integration strategies, metaphor-based partnerships, and evaluation orientations, this study establishes a coherent conceptual foundation for understanding how hybrid design principles evolve across contemporary MH-MH research.

MHs Approach for Solving Optimization Problems

As defined by Glover in 1986, an MH is a senior heuristic designed to identify a heuristic that can provide a rough answer to an optimization challenge. Heuristics and MHs are often used alike in most literature. MHs are used to solve several kinds of problems. In recent times, the name MH has been given to stochastic algorithms that have randomization and local search. It is through randomization that local searches can be diverted to global searches. As such, every MH algorithm searches for the global optimum solution (Gandomi et al., 2013).

MHs has been widely accepted for some time now since it is flexible, simple, tackle local optima, and derivate-free (Avci and Yildirim, 2023). The total performance of a new algorithm may be different based on the domain of the problem for which it is used. The result can be positive or negative when searching for feasible answers to problems using a specific algorithmic process. A MH is not dependent on a problem and is operated based on randomized inputs and outputs obtained. The goal is to provide a practical algorithm that can produce satisfactory and reasonable solutions.

The significant goals of search using MHs are (Nesmachnow, 2014):

1. To achieve goal function values that are close to the optimum or that are appropriate for the computational process to solve optimization challenges efficiently
2. Rather than entering the local optimum, explore the available solutions

Classification of MH Hybrids

Four key factors; namely, the hybridized algorithm, the extent of hybridization, the sequence of execution, and the guiding control strategy are used to categorize MH hybrids (Raidl et al., 2019) (Figure 1).

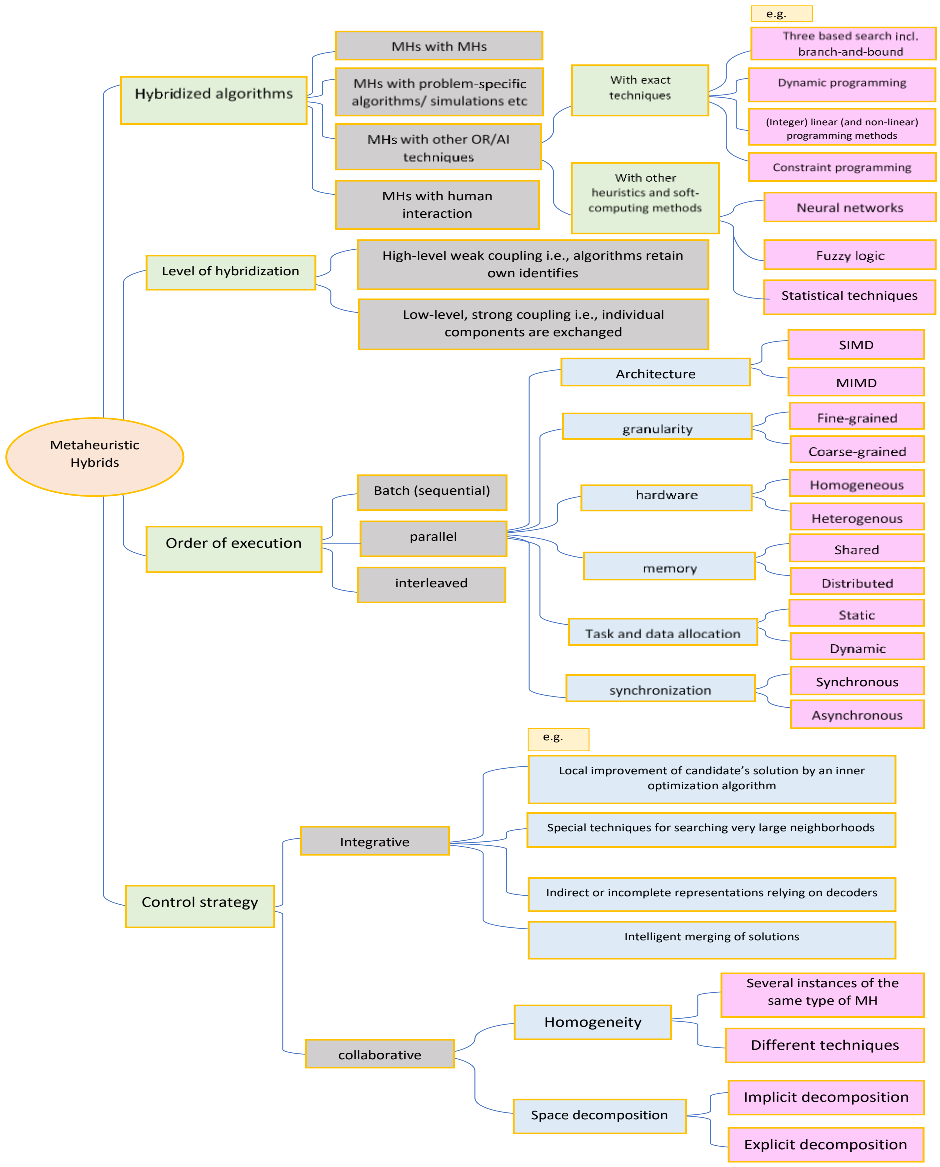

Fig. 1: Classification of Metaheuristic Hybrids (adapted from Raidl et al., 2019)

1. Hybridized algorithms: This encompasses an intricate fusion of diverse MH elements, putting together MHs with bespoke algorithms crafted for specific contexts, and intertwining MHs with other methods from the OR and/or AI realms
2. Level of hybridization: The categorization of MH hybrids delves into the art of integration. In high-level coupling, the essence of the original algorithms is preserved, interacting through a refined interface that gracefully partitions internal workings. Conversely, low-level coupling fosters a robust interplay, intertwining algorithmic components or functions into a harmonious symphony
3. Order of execution: MH hybrids can be classified based on their execution order since they involve the sequential implementation of algorithms, using each algorithm's output as the next one's input. This iterative process ensures convergence criteria are met while maintaining a balanced iteration distribution between the two algorithms. More complex approaches combine algorithms in an interleaved manner so that information is communicated very regularly and in a bidirectional manner. In the parallel approach, two algorithms collaborate, overseeing the same population. An intriguing variation comes into play when one algorithm assumes a designated fraction of the other's workload. Parallel MHs have become a focus of research, and several

classifications have been proposed for hybrid parallel approaches. The distinguished criteria include: architecture, which is either Single Instruction, Multiple Data streams (SIMD) or Multiple Instruction, Multiple Data streams (MIMD); the granularity of parallelization, which is either fine or coarse-grained; the hardware, which is either homogeneous or heterogeneous; the memory, which may be shared or distributed; the task and data allocation, which may be static or dynamic; and whether the execution of parallel processes is asynchronous or synchronous

4. Control strategy: The control strategy may either be integrative (coercive) or collaborative (cooperative). Within the integrative framework, one algorithm assumes the role of a subordinate MH nestled within a masterful counterpart. There are two possible approaches in this category, the first is complete manipulation, in which, in every round, the whole set is carefully fine-tuned. Typically, seamlessly integrating such a sub-function into the current source algorithm is straightforward. In the second approach, partial manipulation, during these adjustments, only a part of the set gets a boost. To ensure the success of these hybrid structures, the key is selecting the right blend and candidate. Collaborative approaches can be grouped into two categories: Homogeneity and space decomposition. Homogeneity can be classified as either homogenous or heterogeneous. A Homogeneous strategy involves running iterations of identical MHs. On the other hand, heterogeneous strategy involves simultaneous execution, comprising multiple iterations of diverse MHs. Space decomposition is classified as either implicit or explicit. Unlike explicit decomposition, which involves separate algorithms exploring distinct search areas, implicit decomposition arises from varied starting points, outcomes, or random choices. The ability to effectively decompose big problems is generally crucial in practice. Sometimes, issues decompose naturally, but mostly it becomes a daunting task, and therefore, self-adaptive schemes may be enforced (Ting et al., 2015)

Problem Statement

Despite extensive progress in MH hybrids' research, limited understanding persists regarding the structural and functional mechanisms that govern how canonical MHs interact within MH-MH frameworks (Blum and Raidl, 2016; Dey et al., 2018). Existing reviews primarily emphasize performance metrics or domain-specific outcomes while overlooking systematic distinctions between genuine MH-MH hybrids and those combining MHs with problem-specific heuristics, operations research techniques, other artificial intelligence methods, or human-in-the-loop mechanisms (Azevedo et al., 2024; Naghavipour et al., 2022). Consequently, the literature provides little clarity on which canonical MHs dominate hybrid design, how their functional roles are distributed between exploration and exploitation across cooperative, sequential, or embedded structures, or how integration strategies are conceptually organized (Boussaïd et al., 2013). Metaphor-classification frameworks exist yet rarely map partner usage or behavioral compatibility in hybrids (Agor et al., 2024a), leaving uncertain whether hybrid combinations are guided by systematic metaphor congruence or empirical convenience. In addition, inconsistencies in evaluation orientation persist, as many studies rely primarily on benchmark testing without linking structural integration to domain applicability (Silva Junior et al., 2024; Kaur et al., 2025). These conceptual and methodological limitations constrain reproducibility and hinder the establishment of unified design principles for MH-MH development.

Research Objectives

1. To identify the three most frequently employed canonical MHs in MH-MH hybridizations within the January to October 2024 corpus
2. To determine the functional roles and integration strategies of the leading MH within MH-MH hybrids, examining how it operates as an exploration or exploitation engine across different integration structures (cooperative, sequential, or embedded)
3. To classify and quantify the hybridization partners of the top three canonical MHs according to their metaphor-based algorithmic families
4. To map and quantify the primary optimization domains in which the top three canonical MHs are applied, highlighting domain concentration and cross-domain generality
5. To distinguish whether hybrids involving the top MHs are predominantly benchmark-driven or domain-driven based on their reported evaluation frameworks

Literature Review

Naghavipour et al. (2022) conducted a systematic mapping of MH hybrids for QoS-aware service composition, classifying 71 studies by algorithmic type and problem domain. While their taxonomy offered a broad synthesis, it conflated MH-MH and Metaheuristic-Machine Learning (MH-ML) hybrids, leaving unexplored the functional roles and structural placements of canonical algorithms, gaps addressed by the current MH-MH-specific review. Kaur et al. (2025) carried out a comprehensive review of single and hybrid MHs in wireless sensor network localization, emphasizing improvements in accuracy and energy efficiency. However, their synthesis remained performance-oriented and lacked codified hybrid classifications or metaphor-based partner analysis, underscoring the need for structural and behavioral mapping as adopted in this study. Jomah and Aji (2024) reviewed swarm intelligence and MH hybrid algorithms for cloud scheduling and demonstrated that hybridization enhanced resource optimization. Nevertheless, their review aggregated algorithmic families without differentiating between cooperative, sequential, or embedded integrations, an analytical dimension central to the present corpus-driven approach. Azevedo et al. (2024) performed a bibliometric and systematic review of hybrid optimization and machine learning methods, tracing 1,007 publications across five decades. Despite its methodological breadth, the study did not isolate MH-MH hybrids or categorize algorithmic metaphors, making the current review's focused treatment of canonical hybrid configurations both novel and necessary. Silva Junior et al. (2024) examined MH applications in aerospace engineering and highlighted the growing adoption of hybrid and swarm-based algorithms such as PSO and GWO. Although domain-specific, their review did not provide a cross-domain structural synthesis or analyze metaphor congruence, both of which the present study operationalized to explain hybrid formation tendencies.

Vora et al. (2018) analyzed MH hybrid approaches for multibiometric authentication systems, demonstrating PSO, GA, and ACO integrations. However, their treatment remained descriptive and did not systematically code algorithmic roles or metaphor alignments, reinforcing the rationale for this study's structured, role-aware hybrid analysis. Collectively, earlier reviews emphasized performance and domain outcomes but did not systematically trace the structural and metaphorical logic underlying hybrid formation. The present study distinguished itself by systematically classifying MH-MH hybrids across five analytical dimensions: Algorithmic frequency, functional role and integration structure, metaphor family, domain mapping and evaluation orientation. To consolidate the methodological gaps identified across previous reviews,

Table 1 compares key studies that informed the present MH-MH synthesis, highlighting the analytical dimensions each addressed or omitted.

Table 1: Summary of Key HM Reviews and Identified Research Gaps

Study	Year	Focus Area	Hybrid Type	Coverage of Current Objectives*	Key Limitation / Gap
Naghavipour et al.	2022	QoS-aware service composition	MH-MH, MH-ML (mixed)	Frequency ✗; Roles ✗; Metaphor ✗; Domain ✓; Evaluation ✗	Conflates hybrid types; lacks structural and functional role mapping
Kaur et al.	2025	Wireless sensor network localization	Single and hybrid MHs	Frequency ✓; Roles ✗; Metaphor ✗; Domain ✓; Evaluation ✗	Performance-oriented; no partner classification or integration analysis
Jomah and Aji	2024	Cloud resource scheduling	Swarm and hybrid MHs	Frequency ✓; Roles ✗; Metaphor ✗; Domain ✓; Evaluation ✓	Aggregates algorithmic families; omits cooperative, sequential, and embedded distinctions
Azevedo et al.	2024	Hybrid optimization and ML synthesis	MH-ML	Frequency ✓; Roles ✗; Metaphor ✗; Domain ✓; Evaluation ✗	Broad bibliometric scope; excludes MH-MH isolation and metaphor taxonomy
Silva Junior et al.	2024	Aerospace and engineering optimization	MH-MH, swarm-based	Frequency ✓; Roles ✗; Metaphor ✗; Domain ✓; Evaluation ✓	Domain-specific; lacks cross-domain generalization and behavioral congruence analysis
Vora et al.	2018	Multibiometric authentication	MH-MH	Frequency ✓; Roles ✗; Metaphor ✗; Domain ✓; Evaluation ✗	Descriptive review; lacks role coding and metaphor-based partner mapping

Methods

This section reports the methodological protocol used to build, screen, extract and analyze the MH-MH hybridization corpus. The procedure follows PRISMA conventions. All counts and percentages reported in the Results were derived from the steps and computations described below.

Study Design and Scope

- Design: Systematic review of MH-MH hybridization studies indexed via Google Scholar
- Corpus used for analysis: N = 105 included studies (final corpus)
- Primary analytic aims reflected in the protocol: Frequency ranking of canonical MHs; focused partner/metaphor classification, domain mapping, evaluation-orientation (benchmark vs domain) for the three leading canonical MH; focused functional and integration-strategy analysis for the leading canonical MH

Search Strategy and Information Sources

- Source: Google Scholar (selected for its inclusive indexing of both journal and high-quality conference literature in computational intelligence)

- Search Period: January 1 - October 31, 2024
- Search logic: The Boolean expression was designed to capture studies that explicitly combine two or more MH algorithms

The search query used was (Metaheuristic or Nature-Inspired or Bio-Inspired or Global or Local or Swarm) and (Metaheuristic or Hybrid or Hybridization or Combination or Integration) and (Optimization or Optimizer or Search) and (Algorithm or Technique or Method or Approach or Strategy).

The logic ensures that only optimization-focused hybrids are retrieved. Searches were repeated with variations including hyphenated and non-hyphenated forms. Terms such as 'nature-inspired' was retained to ensure coverage of recent algorithms with ambiguous naming conventions but verified manually for relevance during screening. Iterative refinement was performed until the top three most frequent MHs (PSO, GWO, WOA) consistently appeared across test retrievals, confirming sufficient recall coverage. All records were exported to a unified spreadsheet for duplicate removal and PRISMA screening.

Screening and Selection (PRISMA Workflow)

- Records identified: N = 1,986
- Duplicates removed: N = 208 → records after deduplication: 1,778
- Title/abstract screening: 1,778 screened → 1,621 excluded
- Full-text assessed for eligibility: 157 → Full-text excluded at this stage
- Reports included in synthesis: N = 105

The numbers provided were used to generate the PRISMA flow diagram shown in Figure 2. The PRISMA flow was adapted from a previous bibliometric scoping review by the authors (Agor et al., 2025), from which MH-ML studies (n = 14) were excluded to isolate the MH-MH subset (n = 105) for comprehensive synthesis.

Eligibility Criteria

Inclusion Criteria

1. Explicit MH-MH hybrid (two or more MH algorithms combined)
2. Application reporting: Paper reports at least one concrete optimization domain or benchmarking context
3. Peer-reviewed (conference or journal) and written in English

Exclusion Criteria

1. Single-algorithm papers and hybrids combining MHs with problem-specific heuristics, operations research techniques, other artificial intelligence methods, or human-in-the-loop mechanisms
2. Non-peer-reviewed sources (preprints without peer review accepted by the community, theses, technical reports) or full text unavailable
3. Duplicate records

Data Extraction and Coding Procedure

All included studies were coded into a master extraction spreadsheet using a standardized extraction form. The lead author performed primary extraction; an independent co-reviewer cross-checked a random 20% sample to confirm consistency. Disagreements were resolved by discussion and, where necessary, senior-author adjudication.

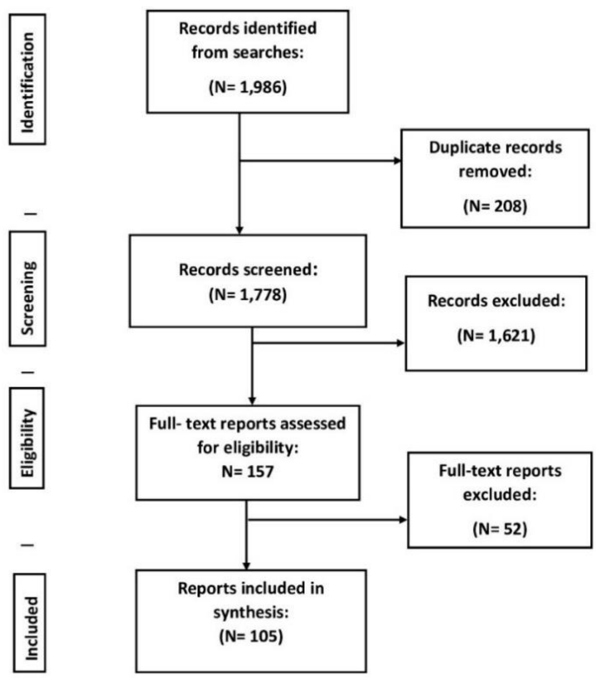

Fig. 2: PRISMA Flow Diagram for MH-MH Hybridization Systematic Review

Extraction Fields (Recorded for Every Study)

- Bibliographic metadata (authors, year, venue, DOI)
- Hybrid label/notation used by paper (e.g., PSO-GWO; SSA-GWO). In instances where the reviewed documents did not provide explicit acronyms or none could be located, standardized abbreviations based on the canonical names of the component MHs were generated solely for consistent tabulation without altering the authors' original attributions
- Canonical MHs involved (explicit names and abbreviations)
- Application domain(s) (detailed labels retained rather than coarse categories)

- Evaluation context: Benchmark-driven (standard mathematical benchmarks/CEC families) vs domain-driven (real-world datasets, system simulations, hardware prototyping) or mixed; evidence cited to justify assignment
- Reported functional role(s) of canonical MH(s) (explicit statements in text/abstract). When absent, the role is coded as Not stated (no inference)
- Integration strategy description (cooperative, sequential, embedded: Coded per definitions below)
- Experimental details (datasets, benchmarks, metrics)
- Quality appraisal flags

Coding Rules (General Principles)

- Conservatism: When the authors state an explicit functional role (exploration/exploitation), code accordingly. If the abstract/text describes only a task without mapping it to exploration/exploitation (e.g., "PSO improved vehicle velocity"), code "Not stated" rather than infer
- Structural analysis scope: Structural integration and role analysis were applied comprehensively for the leading canonical MH (PSO)
- Dual/multiple roles: If an author explicitly assigns numerous roles to an MH (e.g., PSO used for both population initialization and local refinement in different stages), all stated roles were recorded; downstream tallies treat such multi-role assignments as separate documented usages

Definitions and Classification Schemes

Functional-Role Taxonomy

- Exploration: Algorithm role explicitly stated as providing diversity, global search, population diversification, feature-set exploration, and randomization of search
- Exploitation/Refinement: Algorithm role explicitly stated as local search, fine-tuning, convergence acceleration, and result refinement
- Not stated: No explicit mapping in abstract/full text

(Role coding strictly follows author descriptions; no speculative assignment.)

Integration-Strategy Taxonomy

- Cooperative (parallel/complementary): Partner algorithms run concurrently or exchange population/parameter information iteratively (e.g., hybrid where agents share information during the run)
- Sequential (multi-stage, forward or reverse): Algorithms execute in stages (e.g., algorithm A initializes or explores, algorithm B refines). Specify the order when stated
- Embedded (operator-level): One MH is embedded as an operator or update rule inside another algorithm's iteration (e.g., PSO velocity update used inside MFPA loop)

Coding rule: Use the integration description the authors provide; if ambiguous, code as not stated.

Domain Labels (Mapping Rules)

- Domains mapped to fine-grained labels (e.g., "PV MPPT under partial shading", "breast cancer diagnosis (WBCD)", "multi-unit production planning (integer + continuous)")
- During synthesis, these were aggregated into higher-level domains for presentation (e.g., Energy/Power Systems; Biomedical / Medical Imaging / Health Analytics; Robotics & Path Planning)

Evaluation Orientation: Benchmark-Driven vs Domain-Driven

- Benchmark-driven: Primary validation uses widely accepted function suites (e.g., CEC families, classical mathematical functions) or controlled benchmark datasets without system simulation/application context
- Domain-driven: Validation uses real-world datasets, system simulations (e.g., MATLAB/Simulink PV models), hardware prototyping, or direct problem-specific performance metrics in application scenarios
- Mixed: Both benchmark and domain evaluations performed (noted explicitly)

Coding rule: Classify according to the primary evaluation emphasis used by authors to support algorithmic claims (as evidenced in Abstract/Method/Results).

Metaphor-Based Partner Classification

- Partner algorithms were mapped into metaphor groups (e.g., Flying Swarm; Terrestrial Swarm; Aquatic Swarm; Evolution; Plant; Physics-Chemistry; Human)
- Mapping used the taxonomy described in Agor et al. (2024c) and commonly accepted metaphorical classifications. Where a partner appeared ambiguous, classification used the partner's canonical description in the source paper (e.g., "firefly algorithm → flying swarm")
- Each partner label was recorded in full (e.g., "Whale Optimization Algorithm (WOA)"), and its metaphor group was recorded once

Quality Appraisal

Each included study was evaluated against three pragmatic criteria tailored for algorithmic research:

1. Clarity of hybrid description: Does the paper provide sufficient algorithmic detail (pseudo-code, algorithm flow) for reproducibility? (satisfactory/partial/unsatisfactory)
2. Reproducibility of experiments: Are datasets, parameter settings, and experimental configurations reported? (satisfactory/partial/unsatisfactory)
3. Comparative benchmarks/ablation: Does the paper compare the hybrid with baselines and/or provide ablation to isolate hybrid effect? (satisfactory/partial/unsatisfactory)

Quality flags were used in sensitivity analysis. Observations from papers with two or more "unsatisfactory" flags were interpreted cautiously and denoted in tables/footnotes.

Data Analysis and Computational Bookkeeping

- Primary tallies: Frequency counts of canonical MH appearances across the corpus (e.g., PSO count = number of included studies that explicitly use PSO). Percentages computed as (count / N_total) * 100, where N_total is 105 for corpus-level tallies. Example: PSO: 20 / 105 = 19.05% → reported as 19.1% (rounded to one decimal). All rounding reported consistently to one decimal place in Results
- For PSO-specific sub-analyses: Denominator = number of PSO hybrids identified (n = 20). Example: Exploration role frequency = 9 / 20 = 45%
- Integration-strategy tallies for PSO hybrids: Cooperative = 10/20 = 50.0%; sequential = 8/20 = 40.0%; embedded = 2/20 = 10.0%. These percentages were computed using the stated definitions above and reflect direct author descriptions
- Partner-frequency tables: Partners grouped by full-name, then aggregated by metaphor group. Partners that appear in multiple hybrids were counted once per hybrid occurrence (i.e., frequency = number of hybrid studies containing that partner)
- Domain tables: Studies were mapped to domain labels; domain-frequency computed as number of unique studies per domain; percent computed versus the relevant denominator (full corpus or sub-corpus as specified)
- Cross-mapping (integration strategy × functional role): Contingency tables and descriptive statements used to interpret alignment patterns (no inferential statistics applied because items are descriptive and sample sizes per cell are small)

Sensitivity Analysis and Robustness Checks

- Quality-sensitivity check: Repeated primary tallies after excluding studies with two or more "unsatisfactory" quality flags to confirm that dominant patterns (top-3 canonical MHs; partner-frequency ranks; domain concentration) are robust to exclusion of low-quality reports
- Abstract-vs-full-text check: For a random 20% sample, we compared values coded from the abstract only against the full text; divergences were documented and, where systematic bias was identified (e.g., role statements present only in full text), we adjusted coding rules and reported the change
- Inter-rater cross-check: A 20% random sample was independently coded by a second reviewer to ensure coding consistency. Disagreements were resolved by consensus; remaining unresolved cases were adjudicated by the senior author and documented

Note: We do not infer functional roles where authors did not state them. This conservative rule reduces false positive role assignments but increases "Not stated" counts; it is the protocol used throughout.

Results and Discussion

Identification of the Top Three Canonical MHs

Frequency analysis of the MH-MH hybridization corpus (N = 105) identified the PSO, GWO, and WOA as the three most recurrent canonical MHs. In total, 104 distinct MHs appeared across the corpus, with PSO reported in 20 studies (19.2%), GWO in 14 (13.5%), and WOA in 9 (8.7%), together representing over 40% of all hybrids. To maintain clarity and focus, only the top 38 MHs with the highest occurrence counts are visualized as shown in Figure 1. Second-tier algorithms included the Salp Swarm Algorithm (SSA), Harris Hawks Optimization (HHO), and Genetic Algorithm (GA), each appearing six times (≈5.8%), followed by the Sine Cosine Algorithm (SCA) and Chameleon Swarm Algorithm (CSA) with five occurrences (≈4.8%). The remaining MHs appeared in four or fewer studies, confirming a steep dominance curve favoring PSO, GWO, and WOA as the primary canonical MHs underpinning 2024 hybrid design trends.

Functional Roles and Integration Strategies of PSO in HMs

The analysis of twenty PSO-based hybrids examined the algorithm's functional role, integration architecture, and the interaction between both dimensions (Tables 2-4).

The result indicates a nearly balanced distribution of functional roles (Table 2). PSO operates primarily as an exploration driver in nine studies (45%), facilitating global search and population diversification before secondary algorithm refinement (e.g., PSORSA, PSO-GA, PSORSA). In eight hybrids (40%), PSO functions in exploitation or refinement, enhancing local convergence and precision following initial region identification by partner algorithms (e.g., HPS-FFO, HWPSO, PSO-WOA). Three studies (15%) did not explicitly specify PSO's role, reporting only general improvements such as "velocity update" or "performance enhancement."

Analysis of twenty PSO-based hybrids reveals three primary integration architectures: Cooperative, sequential, and embedded (Table 2). Cooperative integration dominated (50%), with PSO operating concurrently or complementarily with partner MHs to maintain convergence stability and population diversity (e.g., PSORSA, HYCHOPSO, HGWOPSO, MHABC-PSO). Sequential integration accounted for 45%, positioning PSO either at the initial stage for global exploration (e.g., PSOGSA, PSO-TS, HPS-FFO) or at the final stage for local refinement (e.g., FFA-PSO, HBBP/HCBP). Embedded integration was observed in 5% of studies (e.g., ITCMSHACPSO, MFPAPSO), where PSO was incorporated as a computational operator within another MH.

Cross-analysis of integration strategy and functional role reveals distinct behavioral patterns (Table 4). Cooperative integrations, which dominate PSO-based hybrids, primarily assign PSO an exploitation or refinement role, leveraging its rapid convergence while partner algorithms sustain diversity (e.g., HWPSO, PSO-WOA). Sequential integrations display a dual configuration: PSO drives exploration when positioned first (e.g., PSO-GA, PSOGSA) and performs local refinement when applied last (e.g., FFA-PSO). Embedded integrations consistently align PSO with localized correction tasks, where its velocity-based updates mitigate stagnation within the host algorithm (e.g., ACO-PSO, MFPAPSO).

Classification and Quantification of Hybridization Partners (Metaphor Families)

Analysis of PSO-based MH-MH hybrids identified 17 distinct partner algorithms across 20 studies (Table 5). FA, WOA, and GWO appeared in two studies each, while the remaining partners occurred once. Flying swarm and terrestrial swarm MHs each accounted for five instances, followed by aquatic swarm (three), and isolated cases of evolution, plant, physics-chemistry, and human algorithms.

Table 6 summarizes the metaphor-based classification and frequency of GWO hybrid partners across 14 studies. PSO and CS appeared in two studies each, while the remaining partners appeared once. Flying swarm MHs accounted for seven instances, terrestrial swarm for two, aquatic swarm for two, and evolution for two.

Table 7 presents the metaphor-based classification and frequency of WOA hybrid partners across nine studies. PSO and FA, classified as flying swarm algorithms, appeared twice each. Terrestrial swarm (CSA, GWO), aquatic swarm (SFO, SSA), human (TLBO), evolutionary (RES), and physics-chemistry (AEO) partners each appeared once.

Mapping Optimization Domains

Table 8 presents the domain mapping of PSO-based hybrids (N = 20). Power systems/energy applications dominate with six studies, including inverter fault detection, solar PV parameter extraction, DC microgrid stability, microgrid control, MPPT, and load frequency regulation. Networking/IoT/cloud computing accounts for four studies, addressing traffic control, cloud load balancing, cloud-fog workflow scheduling, and feature selection. Feature selection/machine learning appears in three studies, biomedical/healthcare in two studies, and robotics/path planning, water/environmental systems, transportation/logistics, clustering/data mining, and finance/forecasting each in a single study.

Table 2: Functional Role of PSO

Study	Hybrid Notation	Functional Role of PSO
Bharath Choudary and Kavithamani (2024)	HPS-FFO	Exploitation / Refinement
Mahesh et al. (2024)	PSO-ALO	Exploration
Subrahmanyam et al. (2024a)	ITCMSHACPSO	Not stated
Singla et al. (2024)	PSORSA	Exploration
Lasabi et al. (2024)	FFA-PSO	Exploitation / Refinement
Mohamed et al. (2024)	HYCHOPSO	Exploration
Najm et al. (2024)	HWPSO	Exploitation / Refinement
Nouh et al. (2024)	CSPSO	Exploration
Zubaidi et al. (2024)	PSOGA	Exploration
Mohapatra et al. (2024)	DPSO	Exploitation / Refinement
Liu et al. (2024)	HBBP/HCBP	Exploitation / Refinement
AIghuraibawi et al. (2024)	MFPAPSO	Exploitation / Refinement
Daouda and Atila (2024)	PSO-TS	Not stated
Shaikh et al. (2024)	HGWPSO	Exploration
Sudha and Maheswari (2024)	PS^2OA	Exploration
Bansal and Aggarwal (2024)	PSO-WOA	Exploitation / Refinement
Iqbal et al. (2024)	MHABC-PSO	Exploitation / Refinement
Subrahmanyam et al. (2024b)	HGWOPSO	Not stated
Chaudhari et al. (2024)	PSOGSA	Exploration
Kuo and Chiu (2024)	HJPSO	Exploration

Table 3: Integration Strategies of PSO

Study	Hybrid	Integration Strategy	Category
Bharath et al. (2024)	HPS-FFO	Sequential execution: PSO optimized network weights before FO refined harmonic minimization	Sequential
Mahesh et al. (2024)	PSO-ALO	Multi-stage cooperative: PSO performed feature exploration; ALO and ACO refined the selected features	Cooperative
Subrahmanyam et al. (2024a)	ITCMSHACPSO	Embedded strategy: PSO embedded in ACO to enhance route selection and velocity optimization	Embedded
Singla et al. (2024)	PSORSA	Cooperative parallel execution: PSO handled global convergence while RSA refined population diversity	Cooperative
Lasabi et al. (2024)	FFA-PSO	Sequential combination: FFA explored search space, and PSO fine-tuned exploitation	Sequential
Mohamed et al. (2024)	HYCHOPSO	Cooperative integration: PSO and CHO ran complementarily for microgrid control	Cooperative
Najm et al. (2024)	HWPSO	Layered cooperation: WOA managed global exploration; PSO refined path optimization	Cooperative
Nouh et al. (2024)	CSPSO	Hybridized cooperation: CS explored diverse areas; PSO improved convergence rate	Cooperative
Zubaidi et al. (2024)	PSOGA	Sequential two-stage: PSO initialized solutions; GA performed refinement through selection and crossover	Sequential
Mohapatra et al. (2024)	DPSO	Cooperative hybrid: PSO guided convergence while DF maintained exploration	Cooperative
Liu et al. (2024)	HBBP/HCBP	Sequential interaction: BES conducted exploration followed by PSO for exploitation	Sequential
AIghuraibawi et al. (2024)	MFPAPSO	Embedded optimization: PSO inserted in MFPA loop to overcome stagnation	Embedded
Daouda and Atila (2024)	PSO-TS	Sequential interaction: PSO performed global search; TS locally refined vehicle routing	Sequential
Shaikh et al. (2024)	HGWPSO	Parallel cooperative: PSO conducted exploration; GWO handled exploitation	Cooperative
Sudha and Maheswari (2024)	PS^{2}OA	Sequential refinement: PSO performed hyperparameter exploration; SSO improved accuracy	Sequential
Bansal and Aggarwal (2024)	PSO-WOA	Cooperative dual-layer: WOA maintained diversity; PSO refined local convergence	Cooperative
Iqbal et al. (2024)	MHABC-PSO	Cooperative control: ABC explored potential regions; PSO accelerated convergence	Cooperative
Subrahmanyam et al. (2024b)	HGWOPSO	Cooperative mechanism: GWO selected features; PSO enhanced convergence and stability	Cooperative
Chaudhari et al. (2024)	PSOGSA	Sequential multi-phase: PSO executed global exploration before GSA performed local refinement	Sequential
Kuo and Chiu (2024)	HJPSO	Sequential: PSO handled parameter optimization; JS refined local solutions	Sequential

Table 4: Cross-Mapping of Integration Strategy and Functional Role

Integration Strategy	PSO Functional Role	Representative Hybrids	Observed Pattern
Cooperative	Predominantly Exploitation / Refinement	PSORSA (Singla et al., 2024), HYCHOPSO (Mohamed et al., 2024), HGWOPSO (Subrahmanyam et al., 2024b), HWPSO (Najm et al., 2024), MHABC-PSO (Iqbal et al., 2024), PSO-WOA (Bansal and Aggarwal, 2024)	PSO refines partner outputs while maintaining convergence stability through synchronized information exchange
Sequential	Mixed, but skewed toward exploration in initial stages	HPS-FFO (Bharath e al., 2024), PSO-GA. (Zubaidi et al., 2024), PSOGSA (Chaudhari et al., 2024), PSO-TS (Daouda and Atila, 2024), PS^{2}OA (Sudha and Maheswari, 2024), HJPSO (Kuo and Chiu, 2024)	When PSO is deployed first, it drives global search and population diversification; when last, it acts as a local refiner
Embedded	Mostly Exploitation / Refinement	ACO-PSO (Nagesh et al., 2024), MFPAPSO (AIghuraibawi et al., 2024)	PSO is mathematically nested within the partner algorithm's equations to stabilize convergence or avoid stagnation

Table 9 presents the domain mapping of GWO-based hybrids (N = 14). Biomedical/medical imaging dominates with four studies, including cancer detection, gene selection, and medical image processing. Engineering optimization follows with three studies covering production planning and design constraints. Energy/power systems and feature selection/machine learning each account for two studies. Single studies are observed in IoT/WSN optimization, robotics/path planning, and control systems. Table 9: Domain Analysis of WOA Hybrids

Table 10 presents the domain mapping of WOA-based hybrids (N = 9). Biomedical/medical imaging and health analytics dominate with three studies, including cancer microarray classification, human activity recognition, and medical image retrieval. Robotics and path planning account for two studies (DWMR trajectory planning and mobile robot path planning). Single studies are observed in energy/power systems, networking/communications, feature selection/data reduction, clustering/data mining, and cloud/workflow scheduling.

Benchmark-Driven vs. Domain-Driven Evaluations

Table 11 presents the evaluation orientation of PSO-based hybrids (N = 20). Fifteen hybrids (75%) were assessed in domain-driven contexts, including energy systems, biomedical datasets, IoT/cloud computing, robotics, and workflow scheduling. Five hybrids (25%) employed benchmark-driven evaluation, using standardized test suites or public datasets such as CEC functions and cancer microarrays.

Table 12 presents the evaluation orientation of GWO-based hybrids (N = 14). Eleven hybrids (78.6%) were assessed in domain-driven contexts, covering biomedical applications, engineering optimization, energy systems, IoT, robotics, and control. Three hybrids (21.4%) employed benchmark-driven evaluation using mathematical function suites or algorithmic testbeds.

Table 13 shows the evaluation orientation of WOA-based hybrids (N = 10). Seven hybrids (70%) were evaluated in domain-driven contexts, covering biomedical analytics, robotics/path planning, energy systems, secure networking, and workflow scheduling. Three hybrids (30%) employed benchmark-driven evaluation using standard test suites (e.g., CEC functions) or extensive benchmark sets.

Across the three canonical MHs, domain-driven evaluation predominates: PSO 75%, GWO 78.6%, and WOA 70%. Benchmark-driven studies constitute a minority for each algorithm: PSO 25%, GWO 21.4%, and WOA 30%.

Table 5: Metaphor-Based Classification and Partner Frequency in PSO Hybrids

Partner (Full name)	Hybrids involving this Partner	Frequency	Metaphor Classification
Firefly Algorithm (FA)	HPS-FFO (Bharath et al., 2024), Hybrid FFA-PSO (Lasabi et al., 2024)	2	Flying swarm
Ant Lion Optimization (ALO)	PSO-ALO (Mahesh et al., 2024)	1	Terrestrial swarm
Ant Colony Optimization (ACO)	ITCMSHACPSO (Subrahmanyam et al., 2024a)	1	Terrestrial swarm
Rat Search Algorithm (RSA)	PSORSA (Singla et al., 2024)	1	Terrestrial swarm
Cheetah Optimization (CHO)	HYCHOPSO (Mohamed et al., 2024)	1	Terrestrial swarm
Whale Optimization Algorithm (WOA)	HWPSO (Najm et al., 2024), PSO-WOA (Bansal and Aggarwal, 2024)	2	Aquatic swarm
Cuckoo Search (CS)	CSPSO (Nouh et al., 2024)	1	Flying swarm
Genetic Algorithm (GA)	PSOGA (Zubaidi et al., 2024)	1	Evolution
Dragonfly Algorithm (DF)	DPSO (Mohapatra et al., 2024)	1	Flying swarm
Bald Eagle Search (BES)	HBBP, HCBP (Liu et al., 2024)	1	Flying swarm
Modified Flower Pollination Algorithm (MFPA)	MFPAPSO (AIghuraibawi et al., 2024)	1	Plant
Tabu Search (TS)	PSO-TS (Daouda and Atila, 2024)	1	Human
Grey Wolf Optimizer (GWO)	HGWPSO (Shaikh et al., 2024), HGWOPSO (Subrahmanyam et al., 2024b)	2	Terrestrial swarm
Snake Swarm Optimization (SSO)	PS^{2}OA (Sudha and Maheswari, 2024)	1	Terrestrial swarm
Artificial Bee Colony (ABC)	MHABC-PSO (Iqbal et al., 2024)	1	Flying swarm
Gravitational Search Algorithm (GSA)	PSOGSA (Chaudhari et al., 2024)	1	Physics-chemistry
Jellyfish Search (JS)	HJPSO (Kuo and Chiu, 2024)	1	Aquatic swarm

Table 6: Metaphor-Based Classification of GWO Hybrid Partners

Partner (Full Name)	Hybrid Name	Frequency	Metaphor Group
Salp Swarm Algorithm (SSA)	SSA-GWO (Rustagi et al., 2024)	1	Aquatic swarm
Differential Evolution (DE)	HE-GWO (Kalananda and Komanapalli, 2024)	1	Evolution
Harris Hawks Optimization (HHO)	GWO-HHO (Alshamlan and Almazrua, 2024)	1	Flying swarm
Aquila Optimizer (AO)	GAOA (Varshney et al., 2024)	1	Flying swarm
Cuckoo Search (CS)	GWO-CSA (Berwal and Kuldeep, 2024), LHCS (Ouyang et al., 2024)	2	Flying swarm
Artificial Bee Colony (ABC)	HABCGWO (Digra et al., 2024)	1	Flying swarm
Particle Swarm Optimization (PSO)	HGWOPSO (Subrahmanya et al., 2024b), HGWPSO (Shaikh et al., 2024)	2	Flying swarm
Bat Algorithm (BA)	BA-GWO (Tbaishat et al., 2025	1	Flying swarm
Shuffled Complex Evolution (SCE)	GWO-SCE (Mosa and Al-Jawher, 2024)	1	Evolution
Red Fox Optimizer (RFO)	RFO-GWO (Ketafa and Al-Darraji, 2024)	1	Terrestrial swarm
Whale Optimization Algorithm (WOA)	GWO-WOA (Thakur et al., 2025)	1	Aquatic swarm
Coati Optimization Algorithm (COA)	COA-GWO (Başak, 2024)	1	Terrestrial swarm

Table 7: Metaphor-Based Classification of WOA Hybrid Partners

Partner (Full Name)	Hybrid	Frequency	Metaphor Group
Chameleon Swarm Algorithm (CSA)	HWOA (Braik et al., 2024)	1	Terrestrial swarm
Teaching-Learning-Based Optimization (TLBO)	TLBO-WOA (Yabalar and Ercelebi, 2024)	1	Human
Particle Swarm Optimization (PSO)	HWPSO (Najm et al., 2024), PSO-WOA (Bansal and Aggarwal, 2024)	2	Flying swarm
Sailfish Optimizer (SFO)	HS-WOA (Goswami et al., 2024)	1	Aquatic swarm
Artificial Ecosystem Optimization (AEO)	AEOWOA (Mostafa et al., 2024)	1	Physics-chemistry
Firefly Algorithm (FA)	FWOA (Tian et al., 2024)	1	Flying swarm
Recombinant Evolutionary Strategy (RES)	RESHWOA (Hafiz and Saeed, 2024)	1	Evolution
Grey Wolf Optimizer (GWO)	GWO-WOA (Thakur et al., 2025)	1	Terrestrial swarm
Shark Smell Algorithm (SSA)	SSA-WOA (Revathi and Kumar, 2024)	1	Aquatic swarm

Table 8: Domain Analysis of PSO Hybrids

Domain	Hybrids	Frequency
Power Systems / Energy	HPS-FFO (Bharath et al., 2024) (fault detection in inverters), PSORSA (Singla et al., 2024) (solar PV parameter extraction), FFA-PSO (Lasabi et al., 2024) (DC microgrid stability), HYCHOPSO (Mohamed et al., 2024) (multiple microgrids control), CSPSO (Nouh et al., 2024) (MPPT in PV under shading), MHABC-PSO (Iqbal et al., 2024) (load frequency control)	6
Biomedical / Healthcare	PSO-ALO (Mahesh et al., 2024) (leukemia prediction), PS^2OA (Sudha and Maheswari, 2024) (lung cancer detection)	2
Networking / IoT / Cloud	ITCMSHACPSO (Subrahmanyam et al., 2024) (IoT traffic control), DPSO (Mohapatra et al., 2024) (cloud load balancing), PSO-WOA (Bansal and Aggarwal, 2024) (cloud-fog workflow scheduling), HGWOPSO (Subrahmanyam et al., 2025) (IoT feature selection)	4
Robotics / Path Planning	HWPSO (Najm et al., 2024) (differential wheeled mobile robot navigation)	1
Water / Environmental Systems	PSOGA (Zubaidi et al., 2024) (urban water demand forecasting)	1

Table 8: Continued

Feature Selection / Machine Learning	HBBP/HCBP (Liu et al., 2024) (feature selection with BES), MFPAPSO (AIghuraibawi et al., 2024) (intrusion detection feature selection), HGWPSO (Shaikh et al., 2024) (feature selection for transmission line modeling)	3
Transportation / Logistics	PSO-TS (Daouda and Atila, 2024) (multi-depot vehicle routing problem)	1
Clustering / Data Mining	PSOGSA (Chaudhari et al., 2024) (data clustering)	1
Finance / Forecasting	HJPSO (Kuo and Chiu, 2024) (stock market trend prediction)	1

Table 9: Domain Analysis of GWO Hybrids

Domain	Hybrids in Domain	Frequency Count
Biomedical / Medical Imaging	SSA-GWO (Rustagi et al., 2024), GWO-HHO (Alshamlan and Almazrua, 2024), BA-GWO (Ting et al., 2015) GWO-SCE (Mosa and Al-Jawher, 2024)	4
Feature Selection / ML	HGWOPSO (Subrahmanyam et al., 2024b), GWO-WOA (Thakur et al., 2025)	2
Engineering Optimization	HE-GWO (Kalananda and Komanapalli, 2024), GAOA (Varshney et al., 2024), LHCS (Ouyang et al., 2024)	3
Energy / Power Systems	GWO-CSA (Berwal and Kuldeep, 2024), HGWPSO (Shaikh et al., 2024)	2
IoT / WSN Optimization	HABCGWO (Digra et al., 2024)	1
Robotics / Path Planning	RFO-GWO (Ketafa and Al-Darraji, 2024)	1
Control Systems	COAGWO (Başak, 2024)	1

Table 10: Domain Analysis of WOA Hybrids

Domain	Studies	Count
Clustering / Data Mining	(Braik et al., 2024) HWOA (K-means clustering)	1
Energy / Power Systems	(Yabalar and Ercelebi, 2024) TLBO-WOA (THD minimization in multilevel inverters)	1
Robotics and Path Planning	(Najm et al., 2024) HWPSO (DWMRs path planning), (Tian et al., 2024) FWOA (mobile robot path planning)	2
Networking / Communications	(Goswami et al., 2024) HS-WOA (secure routing in MANETs)	1
Feature Selection / Data Reduction	(Mostafa et al., 2024) AEOWOA (feature selection with high accuracy)	1
Biomedical / Medical Imaging / Health Analytics	(Hafiz and Saeed, 2024) RESHWOA (cancer microarray + SVM), (Thakur et al., 2025) GWO-WOA (human activity recognition), (Revathi and Kumar, 2024) SSA-WOA (medical image retrieval/classification)	3
Cloud / Workflow Scheduling	(Bansal and Aggarwal, 2024) PSO-WOA (workflow scheduling in cloud-fog computing)	1

Table 11: Evaluation Orientation of PSO Hybrids

Study	Hybrid	Evaluation Context	Category
Bharath et al. (2024)	HPS-FFO	Fault detection in multilevel inverters	Domain-driven
Mahesh et al. (2024)	PSO-ALO	Leukemia gene expression datasets	Domain-driven
Mohamed et al. (2024)	HYCHOPSO	Multi-microgrid control	Domain-driven
Subrahmanyam et al. (2024a)	ITCMSHACPSO	IoT traffic control simulation	Domain-driven
Singla et al. (2024)	PSORSA	PV parameter extraction (benchmark tests)	Benchmark-driven
Lasabi et al. (2024)	FFA-PSO	DC microgrid experiments + eigenvalue analysis	Benchmark-driven (applied)
Najm et al. (2024)	HWPSO	Mobile robot path planning	Domain-driven
Nouh et al. (2024)	CSPSO	PV MPPT under shading	Domain-driven
Zubaidi et al. (2024)	PSOGA	Urban water demand ANN tuning	Domain-driven
Mohapatra et al. (2024)	DPSO	Cloud load balancing	Domain-driven
Liu et al. (2024)	HBBP-HCBP	10 public cancer microarray datasets	Benchmark-driven
AIghuraibawi et al. (2024)	MFPAPSO	IDS dataset (ICMPv6 DDoS detection)	Domain-driven
Janaki et al. (2024b)	HGWOPSO	IoT feature selection datasets	Domain-driven
Daouda and Atila (2024)	PSO-TS	Multi-depot vehicle routing	Domain-driven
Iqbal et al. (2024)	MHABC-PSO	Load frequency control in power systems	Domain-driven
Shaikh et al. (2024)	HGWPSO	CEC19 benchmarks + transmission line capacitance	Benchmark-driven
Sudha and Maheswari (2024)	PS^2OA	Lung cancer medical images	Domain-driven
Bansal and Aggarwal (2024)	PSO-WOA	Workflow scheduling (WorkflowSim toolkit)	Domain-driven
Chaudhari et al. (2024)	PSOGSA	Standard clustering datasets	Domain-driven
Kuo and Chiu (2024)	HJPSO	Stock market prediction datasets	Domain-driven
Ouyang et al. (2024)	LHCS	CEC2017 benchmark functions	Benchmark-driven

Table 12: Evaluation Orientation of GWO Hybrids

Study	Hybrid	Evaluation Context	Category
(Rustagi et al., 2024)	SSA-GWO	Breast cancer diagnosis	Domain-driven
(Kalananda and Komanapalli, 2024)	DE-GWO	Constrained engineering problems (test-based)	Benchmark-driven
(Alshamlan and Almazrua, 2024)	GWO-HHO	Cancer feature selection and classification	Domain-driven
(Varshney et al., 2024)	GAOA	Complex engineering design	Domain-driven
(Berwal and Kuldeep, 2024)	GWO-CSA	Solar photovoltaic (PV) systems	Domain-driven
(Digra et al., 2024)	HABCGWO	IoT energy optimization in WSNs	Domain-driven
(Subrahmanyam et al., 2024)	HGWOPSO	IoT feature selection	Domain-driven
(Tbaishat et al., 2025)	BA-GWO	Gene selection for cancer classification	Domain-driven
(Mosa and Al-Jawher, 2024)	GWO-SCE	Algorithmic optimization (test functions)	Benchmark-driven
(Ketafa and Al-Darraji, 2024)	RFO-GWO	Path planning in autonomous mobile robots	Domain-driven
(Thakur et al., 2025)	GWO-WOA	Human activity recognition	Domain-driven
(Shaikh et al., 2024)	HGWPSO	Power transmission parameter computation	Domain-driven
(Başak, 2024)	COA-GWO	Vehicle suspension tuning	Domain-driven
(Ouyang et al., 2024)	LHCS (GWO variant)	Algorithmic improvement	Benchmark-driven

Table 13: Evaluation Orientation of WOA Hybrids

Study	Hybrid	Evaluation Context	Category
(Braik et al., 2024)	HWOA	Clustering on UCI datasets	Domain-driven
(Yabalar and Ercelebi, 2024)	TLBO-WOA	THD minimization in multilevel inverters	Domain-driven
(Najm et al., 2024)	HWPSO	Mobile robot path planning	Domain-driven
(Goswami et al., 2024)	HS-WOA	Energy-efficient routing in MANETs	Domain-driven
(Mostafa et al., 2024)	AEOWOA	Feature selection on multiple datasets + CEC'20 benchmark	Benchmark-driven
(Tian et al., 2024)	FWOA	Mobile-robot path planning + 23 benchmark functions	Benchmark-driven
(Hafiz and Saeed, 2024)	RESHWOA	SVM parameter tuning on microarray datasets + 13 benchmarks	Benchmark-driven
(Thakur et al., 2025)	GWO-WOA	Human activity recognition	Domain-driven
(Revathi and Kumar, 2024)	SSA-WOA	Content-based medical image retrieval	Domain-driven
(Bansal and Aggarwal, 2024)	PSO-WOA	Workflow scheduling in cloud-fog	Domain-driven

Discussion

The findings derived from the five research objectives collectively illuminate the methodological patterns, design principles, and theoretical directions shaping contemporary MH-MH hybridization. Analysis of the 2024 MH-MH corpus shows that PSO, GWO, and WOA form the structural core of hybrid systems, appearing in over 40% of all identified hybrids. This prevalence reflects a deliberate design preference for canonical, modular algorithms characterized by minimal parameterization, computational efficiency, and well-balanced exploration-exploitation dynamics. These attributes facilitate the development of stable, interpretable hybrid frameworks adaptable across diverse problem domains.

PSO's operational roles across 20 hybrid configurations demonstrate near-equilibrium between exploration (45%) and exploitation (40%), confirming its dual-purpose versatility. Cooperative and sequential integration strategies dominate these configurations, with PSO frequently functioning as the global diversification phase or a local refinement module, depending on its structural positioning. Embedded integrations, though fewer, illustrate PSO's compatibility for mathematical nesting within partner MHs, enabling algorithmic stabilization, mitigation of stagnation, and enhanced convergence performance. This distribution underscores PSO's architectural neutrality and deliberate selection as a functional centerpiece rather than incidental inclusion.

Partner classification reveals that metaphorical congruence underpins hybrid design choices. Across PSO, GWO, and WOA hybrids, flying and terrestrial swarm MHs are the most recurrent metaphor families. Designers preferentially pair algorithms with shared behavioral paradigms, such as velocity-based motion, leader-follower coordination, or adaptive neighborhood updates, to maintain coherent population dynamics. Frequent pairings of PSO with FA, WOA with aquatic/flying swarms, and GWO with flying counterparts such as HHO and BA exemplify this pattern. These combinations ensure convergence stability, reinforce population coherence, and balance exploration and exploitation within hybrid frameworks, reflecting a consistent strategy of behaviorally aligned integration.

Domain mapping further contextualizes hybrid adoption and application focus. PSO-based hybrids are concentrated in power and energy systems (six studies), IoT and network optimization (four), and feature selection (three). GWO-based hybrids primarily target biomedical analytics (four) and engineering optimization (three), whereas WOA-based hybrids span biomedical imaging, robotics, and energy applications. This distribution signals a maturation of MH-MH research, where algorithmic innovation increasingly aligns with domain-specific objectives requiring robustness, adaptability, and real-world operational relevance. Embedded integrations in particular demonstrate structural strategies aimed at enhancing algorithmic stability and preventing stagnation within these applied contexts.

Evaluation orientation corroborates this methodological shift. Across the three canonical MHs, 70-75% of studies are domain-driven, validated through real-world datasets, simulations, or application prototypes, while the remainder employ benchmark functions for comparative calibration. Domain-driven studies ensure applied robustness and generalizability, whereas benchmark-driven evaluations preserve methodological rigor, reproducibility, and cross-algorithm comparability. The coexistence of these approaches indicates an emerging dual-validation logic, synthesizing theoretical precision with practical applicability.

Collectively, these findings highlight three interrelated heuristics shaping contemporary MH-MH hybrid design:

1. Algorithmic complementarity - Canonical MHs such as PSO, GWO, and WOA combine to maintain exploration-exploitation balance through cooperative, sequential, and embedded integrations
2. Metaphor congruence - Partners are selected from compatible metaphor families to ensure behavioral coherence, stabilize search dynamics, and enhance convergence
3. Evaluation coherence - Research increasingly prioritizes domain-grounded optimization over Purely Benchmark-Driven Evaluation, reflecting a strategic focus on real-world relevance and functional robustness

Together, these principles indicate that MH-MH hybridization in 2024 has evolved from ad hoc algorithmic fusion to structured architectural design governed by algorithmic complementarity, metaphorical alignment, and evaluation coherence. These heuristics collectively underpin the emergence of interpretable, behaviorally consistent, and domain-relevant MH-MH hybrids adaptable across complex optimization problems.

This review is limited by its temporal scope, covering publications only from January to October 2024. Additionally, it employs a descriptive, structural synthesis without a quantitative meta-analysis.

Conclusion

This systematic review examined MH-MH hybridization studies published between January and October 2024 to clarify algorithmic dominance, functional and structural roles, metaphorical foundations, domain mapping, and evaluation orientation in hybrid design. Frequency synthesis across 105 identified algorithms confirmed PSO, GWO, and WOA as the dominant MHs. Functional and structural analysis of PSO showed it alternates between global exploration and local refinement and that it is deployed across cooperative, sequential, and embedded integration strategies. Metaphor-based partner analysis indicated that effective hybrids are guided by behavioral congruence, with compatible algorithms from flying and terrestrial swarm families forming stable and efficient pairings. Domain mapping revealed a shift toward applied optimization, with PSO, GWO, and WOA hybrids primarily addressing energy, biomedical, and network problems. Evaluation orientation reflected increasing methodological maturity, as these hybrids adopt domain-driven validation while retaining benchmark testing for theoretical comparability.

Future research should perform multi-year analyses focusing on performance and computational costs. It should also explore self-adaptive MH-MH frameworks with learning-based controllers, multiobjective optimization, and standardized benchmark repositories for consistent empirical evaluation.

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Authors Contributions

Augustina Dede Agor: Conceived and designed the study, led its subsequent revision in response to reviewer comments, coordinated the systematic review methodology, supervised data extraction and synthesis, drafted the original manuscript, led its substantial revision and finalization, managed all revisions, and approved the final version.

Frank Kataka Banaseka: Contributed to data screening and extraction validation, interpretation of findings, critical revision of the methodology and results sections, and approved the final manuscript.

Prince Silas Kwesi Oberko: Contributed to analysis interpretation, validation of figures and tables, critical revision of results presentation, and approved the final manuscript.

Linda Amoako Banning: Contributed to manuscript restructuring, language refinement, critical revision of the discussion and conclusions, and approved the final manuscript.

Stephen Kofi Dotse: Contributed to literature synthesis refinement, conceptual alignment after revision, critical review for intellectual coherence, and approved the final manuscript.

Emmanuel Junior Tapany: Contributed to technical validation of the revised content, reference and formatting checks, critical revision for technical accuracy, and approved the final manuscript.

Ethics

This review article is based on an analysis of publicly available literature, and no primary data collection involving human or animal subjects was conducted. Therefore, no ethical issues are anticipated.

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