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Beyond Trial and Error: A Comprehensive Classification of Metaheuristics along with Metaphor Criterion Development Trend

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Abstract

Objectives: The research aims to develop a comprehensive classification system for metaheuristics, categorize metaphor metaheuristics, and present the development trend and percentage representation of metaphor metaheuristics within each metaphor group. **Method**: A descriptive-based systematic review was conducted to collect data on studies concerning the classification of metaheuristics and the proposal of new metaheuristics. Data was sourced from Google Scholar, Science Direct, Springer, ResearchGate, and IEEE Xplore. For the first research objective, 148 studies were screened, resulting in the selection of six studies. The second and third research objectives involved screening 1145 studies, of which 654 were ultimately selected. This review considers studies published up to August 2023. The extracted data includes the characteristics of each classification and the name, abbreviation, author, year, and metaphor group for each metaheuristic reviewed. **Findings**: The results reveal that existing classifications do not cover the full range of metaheuristic characteristics. The data indicates a rising trend in the introduction of new metaheuristics over the years, with the peak occurring in 2020, boasting 68 new approaches, closely followed by 2022 with 57 introductions. However, between 1965 and 1992, progress was limited to only one or two new approaches annually, signifying periods of stagnation in the field. The majority of metaheuristics proposed are in the physics-chemistry metaphor group (20%), followed closely by human metaheuristics (18%). **Novelty**: The novelty of this study lies in its exhaustive classification of metaheuristics developed from 1965 to August 2023 based on the metaphor criterion, along with the development progression and percentage-wise representation of various metaphor groups using up-to-date data.

Keywords: Metaheuristics; Metaphor; Classification; Optimization; Trend

1 Introduction

Optimization is vital in modern decision-making across diverse fields, enhancing efficiency and performance amidst the upsurge of optimization problems. While exact algorithms are accurate in finding the optimal solution, they tend to be inefficient and time-consuming for complex optimization problems, as their computational time grows exponentially with the problem's dimension. To overcome the limitations of exact methods and address the demand for accuracy and efficiency in finding appropriate solutions, many challenges are solved by trial and error using various optimization techniques. Thus, approximate algorithms, are employed. These algorithms, classified as heuristics and metaheuristics, aim to offer near-optimal solutions swiftly for complex problems.

A heuristic algorithm is used to generate satisfactory solutions for optimization problems by a trial-and-error method. Heuristics are highly dependent on the specific situation they are applied to and may not be effective for solving other problems. In contrast, metaheuristics go beyond the ordinary trial-and-error techniques[1], and so is a more generic improvement over heuristics.

Intensification and diversification, integral to metaheuristics, collaborate to find near-optimal solutions. Intensification involves exploiting local search to focus on a specific area and efficiently find near-optimal solutions in that region. On the other hand, diversification explores the search space globally to discover new solutions and prevent the algorithm from getting stuck in a local optimum[2]. Despite their success in many cases, metaheuristics have limitations and cannot universally solve all optimization problems. Additionally, the No Free Lunch (NFL) theorem suggests that all metaheuristics have the same average performance across all optimization problems[3,4]. The NFL theorem, along with other driving factors, has spurred the emergence of a multitude of metaheuristic algorithms, in particular, metaphor metaheuristics, that are specifically designed to adapt to various types of optimization problems, including continuous, discrete, constrained, unconstrained, multi-objective, single objective and so on.

The proliferation of new metaheuristics in recent years has prompted the necessity for their classification. While various classification schemes have been proposed, existing reviews have limitations. For instance, Rajwar et al.[5] focus primarily on parameter settings, whereas Ma et al.[6] concentrate on population and single-solution metaheuristics. Stegherr[7] overlooks metaphorical criteria. On the other hand, Pazhaniraja et al.[8] incorporate factors for classifying optimization problems in general rather than metaheuristics. Although Akyol and Alatas[9] present a multilevel scheme, they omit consideration of critical factors such as parameterized criteria. Similarly, Anantharaj et al.[10] focus exclusively on nature-inspired criteria.

The proposed classification in this study is a comprehensive scheme that incorporates all the critical factors. With eleven levels, including three levels under the metaphor group. This scheme provides a structured approach for organizing and communicating ideas in the field. Further, this review distinguishes itself by providing an exhaustive list of existing metaheuristics proposed from 1965 to August 2023, totalling 654, each classified under a distinct metaphor group. The categorization of the numerous existing metaheuristics would aid researchers in identifying areas for improvement and selecting the most effective ones for specific optimization problems. Additionally, this study presents the development trends and percentage-wise distribution of these classified metaheuristics. This work is poised to facilitate the development and improvement of new algorithms, offering invaluable insights for researchers[7].

1.1 Statement of the Problem

Despite their value, a comprehensive and up-to-date classification system for metaheuristic algorithms is lacking in the literature, especially one that captures all the diverse landscapes. Furthermore, the absence of a current and thorough categorization hinders researchers' ability to track the development trends and understand the percentage representation of existing metaheuristics within different metaphor groups.

1.2 Objectives

1. To create a comprehensive classification system for metaheuristics.
2. To categorize metaphor metaheuristics.
3. To present the development trend and percentage representation of the metaphor metaheuristics within each metaphor group.

2 Methodology

The systematic literature review undertaken is descriptive. Descriptive reviews analyse the current state of the literature concerning a particular research objective, question, topic, or concept.

2.1 Search Strategy

Two distinct searches were performed to achieve the research objectives. For each, we used all possible combinations of terms from each set. To achieve the first research objective, the combination of keywords used is provided in Figure 1. Set A1 merged with Sets A2, through A5. To accomplish the second and third objectives, the combinations of keywords used for the search are provided in Figure 1. Set B1 was combined with Sets B2, B3 and B4. The keywords used were derived from the research objectives. The concepts in the search statement were taken and extended by synonyms and related terms. For instance, in the first search, Set A1 terms like "Multilevel" or "Comprehensive" or "Extensive" or "Detail" or "Exhaustive" were combined with Set A2 terms such as "Classification" or "Categorization" or "Framework" or "Taxonomy," along with Set A3 terms including "Metaheuristic" or "Nature-inspired" or "Bio-inspired" or "Trial and error" or "Global" or "Local" or "Swarm" or "Higher-level," and Set A4 terms such as "Optimization" or "Optimizer" or "Search" or "Heuristic," and finally, Set A5 terms like "Algorithm" or "Technique" or "Method" or "Approach". Likewise, in the second search, Set B1 terms like "Novel" or "New" were combined with Set B2 terms such as "Metaheuristic" or "Nature-inspired" or "Bio-inspired" or "Trial and error" or "Global" or "Local" or "Swarm" or "Higher-level," along with Set B3 terms including "Optimization" or "Optimizer" or "Search" or "Heuristic," and Set B4 terms such as "Algorithm" or "Technique" or "Method" or "Approach".

2.2 Exclusion keywords

The keywords excluded include hybrid, enhance, improve, advance, adaptive, chaotic, variant, augmented lagrangian, fuzzy logic, binary encoding, and quantization.

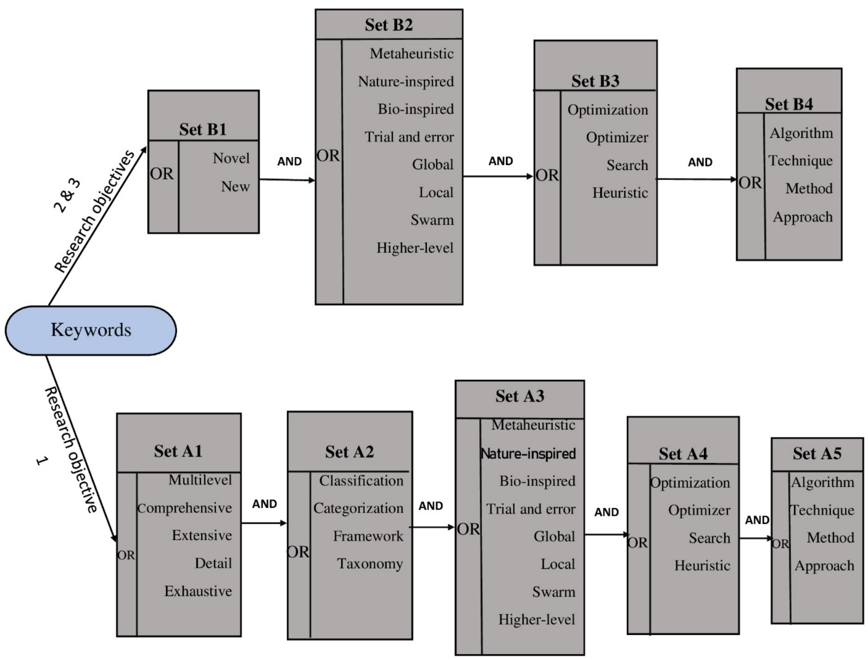

Fig 1. Search keywords combinations

2.3 Research Resources

The systematic literature search drew from multiple databases. The following digital libraries were used to search for the needed research studies since no database includes the complete set of published materials: Google Scholar, Science Direct, Springer, ResearchGate, and IEEE Xplore. Forward search was conducted to identify relevant work cited by the articles and backward searches were conducted to find all articles that have since cited the articles reviewed. Figure 2 and Figure 3 provide the number of documents reviewed per database for each search.

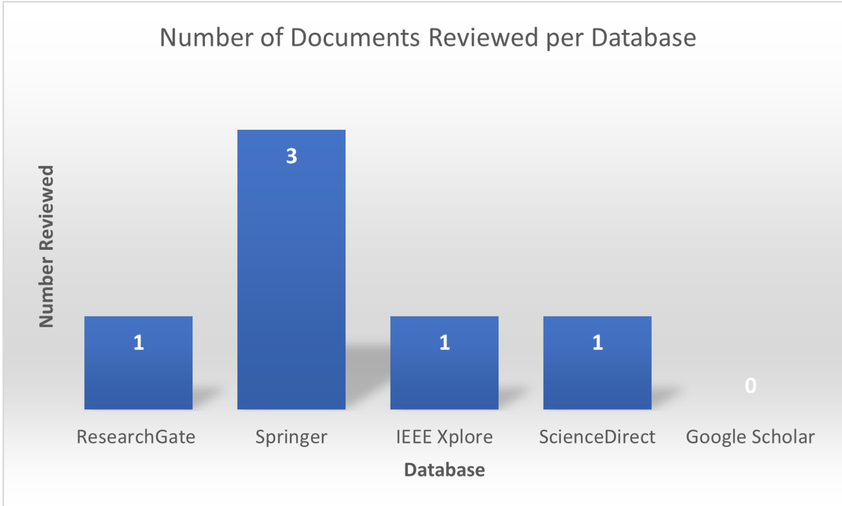

Fig 2. Number of documents reviewed per database for first search

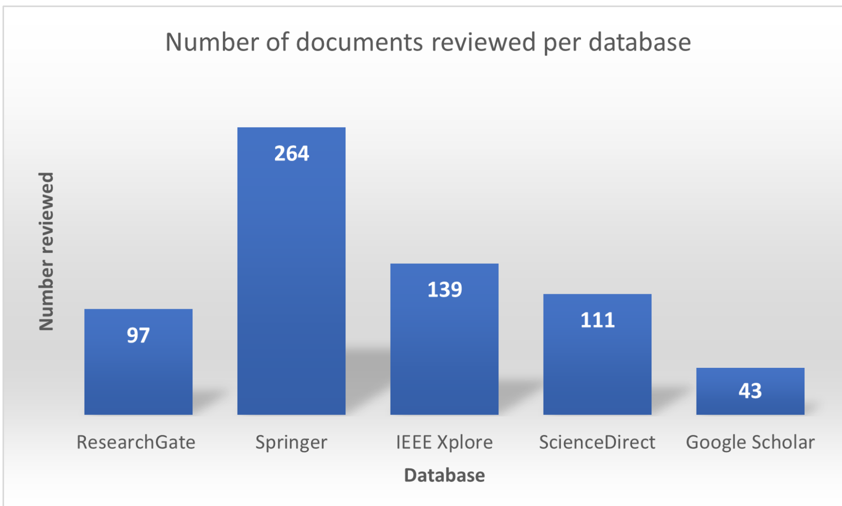

Fig 3. Number of documents reviewed per database for the second search

2.4 Inclusion criteria screening

Regarding the first research objective, 148 research materials were obtained from the mentioned resources using the search keywords while the second search had 1145 results regarding the second and third objectives. Further, filtration was done by the authors to ensure only the valid and relevant materials were included as shown in Figure 4. The filtration included:

1. Publication must be in English language.
2. The year limit should be up to August 2023.
3. Read the title and select studies that relate to the research.
4. Read the abstract and conclusion of each paper and remove the irrelevant and duplicate.
5. Read the full research paper and choose the ones relevant to the topic.

2.5 Data Extraction Strategy

For research objective 1, the data extracted were the descriptive characteristics of each metaheuristic classification. For research objectives 2 and 3, the data extracted include the name, abbreviation, author, year and metaphor group.

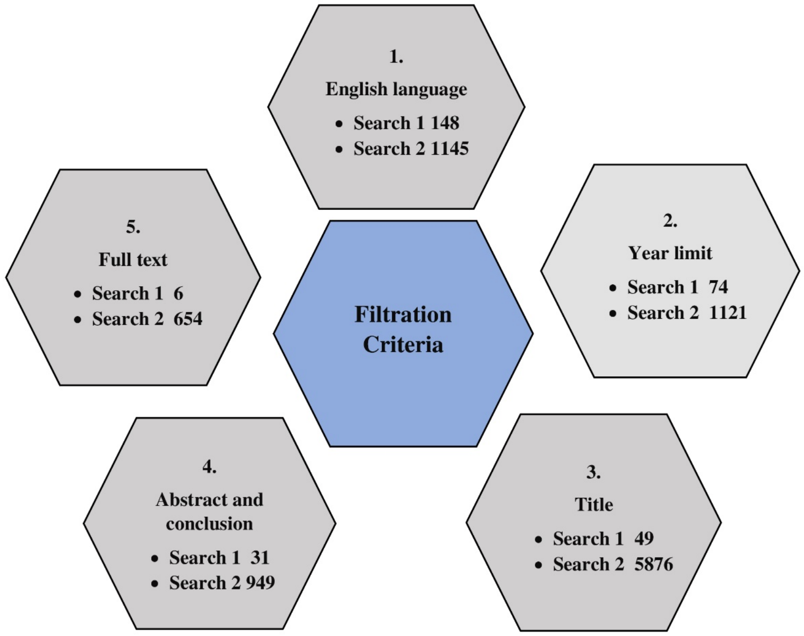

Fig 4. Filtration criteria

3 Results and Discussion

3.1 Research objective 1: Classification of metaheuristics

Rajwar et al.[5] emphasize the significance of parameter settings in metaheuristics, highlighting that the performance of these algorithms heavily relies on the chosen parameter values. They discuss the intricate nature of parameter tuning and propose a classification framework based on the number of primary control parameters employed in the algorithms: Free-parameter-based algorithms (FPAs) for 0 parameters, Mono-parameter-based algorithms (MPAs) for 1 parameter, Bi-parameter-based algorithms (BPAs) for 2 parameters, Tri-parameter-based algorithms (TrPAs) for 3 parameters, Tetra-parameter-based algorithms (TePAs) for 4 parameters, and Penta-parameter-based algorithms (PPAs) for 5 parameters. A miscellaneous category is designated for algorithms with more than five parameters. Their classification is limited to parameter settings.

Ma et al.[6] provide a tabulation of over 500 metaheuristics, conduct a comparative analysis of 11 newly proposed algorithms and 4 state-of-the-art algorithms on benchmark problems, statistically examine their performance, investigate search bias, and identify efficient and robust algorithms. Before these, the authors present a rough classification of metaheuristics into population-based optimization algorithms (POAs) and single-solution-based optimization algorithms (SOAs) with POAs further categorized as evolutionary algorithms (EAs), swarm intelligence algorithms (SIAs), and physics or chemistry-based algorithms (P/CBAs). The number of solutions for each algorithm iteration is the primary factor used. The 500-plus metaheuristics listed were not categorized. The suggested classification system does not take into account the following criteria: hybrid and non-hybrid, parameterized and non-parameterized, deterministic and stochastic, one-neighbourhood and multi-neighbourhood, local and global search, memory and memoryless, and single and multi-objective function.

Stegherr et al.[7] propose a classification system for metaheuristics. The system consists of seven levels: structure, behaviour, search, algorithm, specific features, evaluation, and metaheuristic, each with specific criteria commonly used in previous classification schemes. The paper illustrates the application of the proposed system by classifying only three basic metaheuristics (genetic algorithm, evolution strategy, and tabu search) based on the criteria from the structure, behaviour, search, and algorithm levels. The authors could not classify the selected three based on the criteria of specific features, evaluation, and metaheuristic levels. The proposed classification does not consider the metaphor and non-metaphor, and hybrid and non-hybrid criteria.

Abdel-Basset et al.[11] provide a categorization of metaphor-based metaheuristics into various groups: biology, chemistry, music, math, physics, and social and sports. The authors compile a list of metaphor-based and non-metaphor-based metaheuristics while providing examples of each category. However, given the evolving nature of the field since the paper's publication in 2018, there may have been significant breakthroughs and advancements leading to the development of new metaphor-based metaheuristics not included in their list. Therefore, updating the paper's inventory of metaphor-based metaheuristics to reflect recent advancements could be imperative. Further, the classification system does not consider static objective function and dynamic objective function, local search and global search, hybrid and non-hybrid, and parameterized and non-parameterized criteria.

The factors delineated by Pazhaniraja et al.[8] encompass various elements crucial for optimization problem analysis, including constraint presence, the problem's physical structure (optimal control, non-optimal control, etc.), equation type (linear, quadratic, polynomial, nonlinear), decision variable value domain (integer or real-valued), variable nature (deterministic or stochastic), function separability, and the number of objective functions. Factors are generally for classifying optimization problems and not metaheuristics.

Akyol and Alatas[9] developed a multi-level classification scheme for metaheuristics. The first level includes physics, social, music, chemistry, biology, sports, math and hybrid-based methods, while the second level involves single and multi-point methods. The third level has a fixed objective function and a variable objective function. The single neighbourhood and variable neighbourhood structures are at the fourth level while the fifth level has memory and memoryless methods. The classification scheme does not account for parameterized and non-parameterized, nature-inspired and non-nature-inspired, local and global search, and greedy and iterative criteria.

Anantharaj et al.[10] categorize nature-inspired algorithms into four groups: evolutionary, physical, swarm intelligence, and bio-inspired, with an extra category for others. The study is limited to nature-inspired criteria.

Birattari et al.[12] proposed a classification scheme to categorize metaheuristics. The factors considered include trajectory and discontinuous, population-based and single-point search, memory usage and memoryless, one and various neighbourhood structures, dynamic and static objective function, and nature-inspired and non-nature-inspired criteria. The classification system does not consider hybrid and non-hybrid, parameterized and non-parameterized, greedy and iterative, local and global search, and metaphor and non-metaphor criteria.

Table 1. Review of metaheuristic classification

Citation	Characteristics	Limitation
[5]	Number of control parameters	-Limited to parameter settings
[6]	Population (evolutionary, swarm intelligence, and physics/chemistry-based) and single solution optimization	-The list was not categorized -Does not consider hybrid and non-hybrid, parameterized and non-parameterized, deterministic and stochastic, one-neighbourhood and multi-neighbourhood, local and global search, memory and memoryless, and single and multi-objective function criteria
[7]	Structure, behaviour, search, algorithm, specific features, evaluation and metaheuristic	-Does not consider metaphor and non-metaphor, and hybrid and non-hybrid criteria.
[11]	Metaphor and non-metaphor-based, nature-inspired and non-nature inspired, trajectory and population-based, deterministic and stochastic, one and multi-neighbourhood structure, iterative and greedy, and memory usage and memoryless criteria.	-List must be updated -Does not consider static objective function and dynamic objective function, local search and global search, hybrid and non-hybrid, and parameterized and non-parameterized criteria.
[8]	Physical structure, equation type, decision variable value domain, variable nature, function separability, and the number of objective functions	-Generally, for classifying optimization problems but not metaheuristics
[9]	Biology, physics, social, music, chemical, sports, mathematics, swarm, hybrid, single-point and multi-point, fixed and variable objective function, single neighbourhood structured, variable neighbourhood structured, and memory and memoryless	-Does not consider parameterized and non-parameterized, nature-inspired and non-nature-inspired local and global search and greedy and iterative criteria
[10]	Nature-inspired: Evolutionary, physical, swarm intelligence, and bio-inspired, others	-Limited to nature-inspired criterion.

Continued on next page

Table 1 continued

[12]	Trajectory and discontinuous, population-based and single-point search, memory and memoryless, one neighbourhood and multi-neighbourhood structures, dynamic and static objective functions, and nature-inspired and non-nature-inspired	-Does not consider hybrid and non-hybrid, parameterized and non-parameterized, greedy and iterative, local and global search, and metaphor and non-metaphor criteria.

3.2 Proposed classification of metaheuristics

Metaheuristic algorithms are best classified based on how they operate within the search space and the metaphor of the search procedures. Figure 5 depicts the classification of metaheuristics.

The classes of metaheuristics are:

- Metaphor vs. non-metaphor

Non-metaphor and metaphor metaheuristics are the two classifications of metaphor-based metaheuristics. Metaphor metaheuristics mimic natural mechanisms, and human behaviour in real life, mathematics, etc. Non-metaphor metaheuristics do not employ the simulation of natural mechanisms for defining the search strategy[11]. The metaphor metaheuristics are human, sports, music, physics-chemistry, maths, and bio metaheuristics. Refer to Table 2 for the groupings of all six hundred and fifty-four (654) metaheuristics that fall under these metaphor classes.

- Human Metaheuristics

These metaheuristic algorithms mimic human behaviour, opinions, activities, and social interactions using mathematical simulations of these phenomena[13]. Researchers design the algorithms by evaluating the activities of human beings bearing in mind that every human has his way of doing things which might affect his or her performance. Well-known algorithms in this category are the election-based optimization algorithm[14], and the Great Wall Construction algorithm[15].

- Sports Metaheuristics

Sports metaheuristics is a strong tool for solving optimization in sports or games[16]. Optimization is relevant in every area of sports such as optimal line-ups, team selection, object detection, scheduling and ranking, data mining for predictions in sports, player recovery mechanisms, performance analysis, and manufacturing of sports outfits and types of equipment. Sports metaheuristics are also referred to as game metaheuristics. Some proposed metaheuristics include the quad tournament optimizer[17] and squid game optimizer[18].

- Music Metaheuristics

Rules, concepts, processes and activities in music have inspired some metaheuristic algorithms. Harmony search[19] is the first music-based metaheuristic algorithm founded on the processes to enrich the harmonies of music. It is an algorithm created to improve the processes of musicians. Melody search algorithm[20] was established to enhance the effectiveness of the harmony search algorithm.

- Physics-chemistry Metaheuristics

The concepts of physics and chemistry also inspired scientists to create the physics-chemistry group. Algorithms that deal with the movement of water, gravitation forces, electromagnetism and electric charges form the physics aspect of this group. Algorithms that are known for the fact that they replicate chemical phenomena such as the movement of particles of gases and chemical reactions form the chemistry aspect of this group.

- Maths Metaheuristics

This group of metaheuristics is inspired by the concepts and rules in mathematics. Examples include the subtraction-average-based optimizer (SABO)[21], exponential distribution optimizer (EDO)[22], and tangent search algorithm (TSA)[23].

- Bio Metaheuristics

Bio metaheuristics are founded on the principles of biological evolution and are classified as plant, swarm intelligence, and evolutionary algorithms. Plant algorithms are introduced into the search field by the metaheuristics of plants. The agents in this category do not communicate among themselves as happens in other categories such as the swarm intelligence-based subgroup. A typical example is the plum tree algorithm (PTA)[21] which takes its inspiration from the biology of the plum trees. The name makes evolutionary algorithms comprehensible. This category takes its inspiration from natural evolution. To start their process, a random populace of solutions is initially generated. The optimum solutions are combined to form new solutions by applying mutation and crossover. The Algorithms of this category have several individuals that can breed and produce new descendants. The breeding nature of the algorithms within this category makes it distinctive. The famous algorithm belonging to the evolutionary subgroup is the genetic algorithm[22] which was inspired by Darwin's theory of evolution and proposed initially by John Holland in the 70s. Algorithms based on the reproduction of several biological organisms such as weeds and queen bees are also in this group.

Swarm intelligence (SI) is an established concept in research and was first proposed by Gerardo Beni and Jing Wang in 1989. SI is the group behaviour of self-organized and decentralized systems living in natural or artificial environments. The concept was initially presented in robotics settings but has been used generally for some time now to signify the development of a group of intelligence from a collection of simple agents ruled by simple rules of behaviour. The bioinspired aspect of SI has stimulated the creation of many SI metaheuristics. SI-based algorithms are first categorized by the kind of animal and foraging and movement patterns inspiring each metaheuristic. Thus, the subcategories of SI algorithms are the aquatic animals, flying animals, microorganisms, and terrestrial animals' metaheuristics. The aquatic animals' metaheuristics are inspired by how aquatic animals like fish schools move and forage. The movement of flying animals like birds is the stimulus for flying animals' metaheuristics. The metaheuristics of microorganisms are derived from those of algae, viruses, bacteria and related species. The metaheuristic of terrestrial animals is motivated by how land animals forage and hunt. The various subgroups under SI algorithms are discussed:

- Aquatic Animals Metaheuristics

This subgroup of metaheuristics is inspired by the aquatic ecosystem of animals like krill herds, dolphins and so on. Some typical algorithms of this group include leopard seal optimization[23] and walrus optimization algorithm[24]

- Flying Animals Metaheuristics

This group of metaheuristic algorithms is inspired by the movements of birds, bats and other insects that fly. Some of the popular algorithms in this sub-group are the mantis search algorithm[25] and the nutcracker optimization algorithm[26]

- Microorganisms Metaheuristics

The metaheuristic algorithms based on microorganisms are connected to how bacteria move to find food. As soon as the bacteria find and eat food, they split apart to look for more in their surroundings. Another group are connected to the virus, like the coronavirus metamorphosis optimization[27].

- Terrestrial Animals Metaheuristics

This subgroup of metaheuristics takes its inspiration from the movements or foraging of terrestrial animals. A typical example is the ant colony optimization metaheuristic algorithm which imitates how ants locate sources of food and inform other ants in the colony about the existence of the food sources. Other algorithms included in this subcategory are the coati optimization algorithm[13] which replicates the natural behaviours of coatis and the dung beetle optimizer[28] which is motivated by the ball-rolling, dancing, foraging, stealing, and reproduction behaviours of dung beetles.

- Nature-inspired methods vs. non-nature-inspired methods

The algorithms that imitate processes inspired by nature are known as nature-inspired algorithms. Methods such as ant colony optimization, lion optimization, and whale optimization are inspired by the natural world. The algorithms that do not imitate processes of nature are classified as non-nature-inspired such as the tabu search[29]

- Single vs. population metaheuristics

The number of solutions involved at a time would determine whether the metaheuristic is single-based or population-based. Single metaheuristics algorithms start with a single candidate solution and are enhanced in iterations. The single methods are also referred to as the trajectory methods. Simulated Annealing[30] is one of the first wave metaheuristic algorithms that involves steps motivated by annealing; a thermal process that reaches low free energy states in a solid through repeated heating and slow cooling phases. Another well-known example is the greedy randomized adaptive search procedure[31]. The population metaheuristic algorithms perform optimization using a set of solutions or populations. In population methods, the search processes are done as an evolution of a group of points like evolutionary computation[32] or evolution of a probability distribution over the search space like ant colony optimization[33].

- Deterministic vs. stochastic

Here we distinguish between two decision-making rules based on randomization namely, deterministic and stochastic (combinatorial). Most of the optimization methods used in practice are stochastic. A typical example of a deterministic approach is a basic local search in which an algorithm substitutes a starting solution with a better one. Stochastic problems have uncertain or dynamic information included in their parameters. The objective function value and violation of constraints are some random variables. Assessment of an objective function value of a solution is done either exactly or approximately or based on Monte Carlo simulation. An example of a stochastic algorithm is simulated annealing [30] in which the solution election is induced probabilistically depending on the values associated with the objective functions.

- One vs. various neighbourhood structures

Most metaheuristic algorithms employ solutions whose neighbourhood structure is single. The topology of the search landscape does not vary as the algorithm is executed. Some metaheuristics such as variable neighbourhood search[34] use several neighbourhood structures that allow alternating among various search landscapes.

- Local vs. global search

Metaheuristics can be classified based on the search procedures namely local or global search metaheuristics. Local search metaheuristics are created based on the structure of a distinct single neighbourhood. This describes the nature of permitted movements, generally starting with a neighbourhood till a local optimum is identified and a strategy is employed to direct the search to another point in the search space. Some hybrid methods, however, associate local search techniques with global search or population metaheuristics. Local methods are mostly exploitative whereas global search methods are explorative.

- Greedy vs. iterative

Another vital group of metaheuristic algorithms is iterative algorithms. These algorithms work in the solutions space of the problem and are put into two groups; single-based algorithms and population-based algorithms based on the number of alternative solutions generated and estimated. Greedy algorithms generally construct a solution piece by piece, by choosing the best local optimal solution in the hope that it generates the best global optimal solution. Such algorithms do not produce optimal solutions always. A typical example of a greedy algorithm is a greedy search genetic algorithm[35]. A metaheuristic algorithm can incorporate iterative and greedy factors, such as in[36].

- Memory vs. memoryless

A key criterion for classifying metaheuristics is the use of search history. Methods that use the completed portion of the search are methods with memory. On the other hand, memory-less methods depend on the current solution to determine where to search in subsequent iterations. Even memory-based algorithms are classified as short-term or long-term memory algorithms. A few iterated solutions are kept in short-term memory instead of long-term memory algorithms which keep lots of data on iterated solutions. Currently, memory has become an important aspect of designing an effective metaheuristic. Typical examples of memory metaheuristics include memory-based hybrid CSA with particle swarm optimization algorithm[37] and dual memory simulated annealing algorithm[38].

- Static vs. dynamic objective function

Metaheuristics are categorised as dynamic or static based on how their objective function is applied. An algorithm that does not vary its' objective function when executed is static whereas one that varies its objective function is dynamic. The goal is to have the chance to search a new region in the search space when local optima are identified. An example of a problem solved using a dynamic objective function is described in[39].

- Non-hybrid vs. hybrid

Hybrid metaheuristics have proved to be effective at solving hard problems. Combining two or more metaheuristics through hybridization has yielded higher performance than a singular method. The number of algorithms to hybridize, the type of algorithms to hybridize, the order of execution and the level of hybridization are the four important factors that must be considered in designing a new hybrid metaheuristic algorithm [40]. Typical examples of hybrid metaheuristics include hybrid cat and particle swarm optimization (CPSO) [41] and beam-ACO [42].

- Non-parameterized vs. parameterized metaheuristics

Parameter settings impact the value of metaheuristics. The population size and iteration count impact nearly all metaheuristics, but they have no direct effect on the algorithm's internal workings. Metaheuristics are classed as parameterized or non-parameterized based on their internal operations. Non-parameterized metaheuristics, adaptable and straightforward in design, efficiently tackle diverse optimization challenges. Vortex search optimization (VS), black hole algorithms (BH), and symbiotic organism search (SOS) are a few examples of non-parameter metaheuristics. On the other hand, parameterized metaheuristics are designed to balance exploration and exploitation during different stages of algorithm execution. The majority of metaheuristics fall into the parameterized category. Typical examples include the spring search algorithm (SSA) [43], and the flower pollination algorithm (FPA) [5].

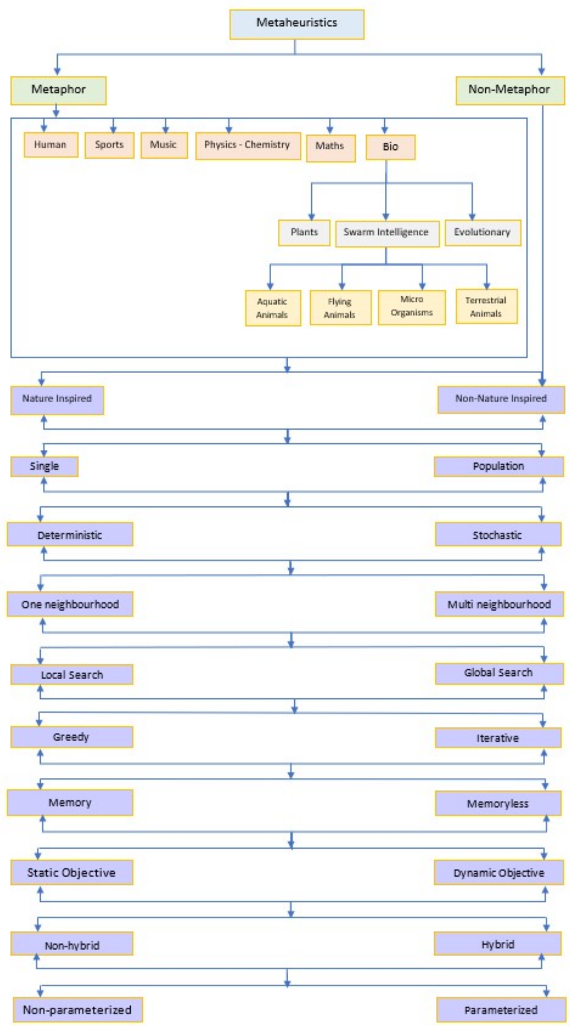

Fig 5. Classification of metaheuristics

3.3 Research objective 2: 654 metaheuristics dating back from 1965 to August 2023 are classified in the various metaphor groups

Table 2. Classification of metaheuristics based on metaphor

No	Metaphor metaheuristic	Year
	Human metaheuristics	
1	Anti-Coronavirus Optimization Algorithm (ACVO)	2022
2	Adaptive Social Behaviour Optimization (ASBO)	2013
3	Adolescent Identity Search Algorithm (AISA)	2020
4	Algorithm of the Innovative Gunner (AIG)	2019
5	Ali baba and the Forty Thieves Optimization (AFT)	2022
6	All Members-Based Optimizer (AMBO)	2021
7	Anarchic Society Optimization (ASO)	2012
8	Artificial Showering Algorithm (ASA)	2015
9	Artificial Tribe Algorithm (ATA)	2010
10	Baby Search Algorithm (BSA)	2021
11	Brain Storm Optimization (BSO)	2011
12	Bus Transportation Algorithm (BTA)	2019
13	Buyer Inspired Meta-Heuristic Optimization Algorithm (BIMA)	2020
14	Chef-Based Optimization Algorithm (CBOA)	2022
15	City Council Evolution (CCE)	2022
16	Clan-based Cultural Algorithm (CCA)	2019
17	Cognitive Behaviour Optimization Algorithm (COA)	2016
18	Cohort Intelligence Algorithm (CI)	2017
19	Collective Decision Optimization Algorithm (CDOA)	2017
20	Community of Scientist Optimization (CoSO)	2012
21	Competitive Optimization Algorithm (COOA)	2016
22	Consultant-Guided Search (CGS)	2010
23	Cooperation Search Algorithm (CSA)	2021
24	Coronavirus Mask Protection Algorithm (CMPA)	2023
25	Creativity-Oriented Optimization Model (COOM)	2015
26	Cultural Algorithm (CA)	2011
27	Dark Forest Algorithm (DFA)	2023
28	Deep Sleep Optimiser (DSO)	2023
29	Doctor and Patient Optimization (DPO)	2020
30	Drawer Algorithm (DA)	2023
31	Driving Training-Based Optimization (DTBO	2022
32	Duelist Optimization Algorithm (DOA)	2016
33	Dynastic Optimization Algorithm (DOA)	2020
34	Election Algorithm (EA)	2015
35	Election Based Optimization Algorithm (EBOA)	2022
36	Election Campaign Algorithm (ECA)	2010
37	Election Survey Algorithm (ESA)	2010
38	Exchange Market Algorithm (EMA)	2014
39	Find-Fix-Finish-Exploit-Analyze Metaheuristic (F3EA)	2017
40	Fireworks Optimization Algorithm (FAO)	2010
41	Following Optimization Algorithm (FOA)	2020
42	Forensic-Based Investigation (FBI)	2020
43	Future Search Algorithm (FSA)	2019
44	Gaining Sharing Knowledge-based algorithm (GSK)	2020
45	Giza Pyramids Construction (GPC)	2021
46	Global-Best Brain Storm Optimization Algorithm (GBSO)	2017
47	Grammatical Evolution Algorithm (GEVA)	1997
48	Great Wall Construction Algorithm (GWCA)	2023
49	Greedy Politics Optimization Algorithm (GPO)	2014
50	Group Counseling Optimization (GCO)	2014

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51	Group Leaders Optimization Algorithm (GLOA)	2011
52	Group Learning Algorithm (GLA)	2023
53	Group Optimization (GO)	2020
54	Group Teaching Optimization Algorithm (GTOA)	2020
55	Growth Optimizer (GO)	2023
56	Heap-based Optimizer (HBO)	2020
57	Human Behavior-based Optimization (HBBO)	2017
58	Human Behaviour-Based Optimization (HBOA)	2021
59	Human Evolutionary Model (HEM)	2007
60	Human Group Formation Algorithm	2010
61	Human Learning Optimization (HLO)	2015
62	Human Mental Search (HMS)	2017
63	Human Urbanization Algorithm (HUA)	2020
64	Human-Inspired Algorithm (HIA)	2009
65	Ideology Algorithm (IA)	2017
66	Imperialist Competitive Algorithm (ICA)	2007
67	Intelligent Ice Fishing Algorithm (IIFA)	2021
68	Interactive Autodidactic School (IAS)	2020
69	Interior Search Algorithm (ISA)	2014
70	Jaya Algorithm (JA)	2016
71	Kidney-inspired Algorithm (KA)	2017
72	Leader-Advocate-Believer Based Optimization (LAB)	2022
73	Leaders and Followers Algorithm (LFA)	2015
74	Life Choice-Based Optimizer (LCBO)	2020
75	Migration Algorithm (MA)	2023
76	Mother Optimization Algorithm (MOA)	2023
77	Mountaineering Team-Based Optimization (MTBO)	2023
78	Nomadic People Optimizer (NPO)	2020
79	Old Bachelor Acceptance (OBA)	1995
80	Open Source Development Model Algorithm (ODMA)	2016
81	Parliamentary Optimization Algorithm (POA)	2008
82	Pastoralist Optimization Algorithm (POA)	2021
83	Political Optimizer (PO)	2020
84	Poor and Rich Optimization (PRO)	2019
85	Queuing Search Algorithm (QS)	2018
86	Real Estate Market-Based Optimization Algorithm (REMARK)	2022
87	Reincarnation Algorithm (RA)	2010
88	Running City Game Optimizer (RCGO)	2023
89	School-Based Optimization (SBO)	2018
90	Search and Rescue Optimization (SAR)	2020
91	Search In Forest Optimization (SIFO)	2022
92	Seeker Optimization Algorithm (SOA)	2007
93	Selfish Herd Optimizer (SHO)	2020
94	Sewing Training-Based Optimization (STBO)	2022
95	Shuffled Shepherd Optimization (SSO)	2020
96	Simple Human Learning Optimization Algorithm (SHLO)	2014
97	Skill Optimization Algorithm (SOA)	2023
98	Social Behavior Optimization Algorithm (SBO)	2003
99	Social Cognitive Optimization Algorithm (SCOA)	2010
100	Social Emotional Optimization Algorithm (SEA)	2010
101	Social Engineering Optimization (SEO)	2017
102	Social Group Optimization (SGO)	2016
103	Social Network Search (SNS)	2021
104	Society and Civilization (SC)	2003
105	Socio Evolution and Learning Optimization Algorithm (SELO)	2018
106	Sperm Motility Algorithm (SMA)	2017

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107	Stochastic Focusing Search (SFS)	2008
108	Success History Intelligent Optimizer (SHIO)	2022
109	Supply-Demand-Based Optimization (SDO)	2019
110	Teaching-Learning Based Optimization Algorithm (TLBO)	2011
111	Team Effectiveness Based Optimization (TEBO)	2017
112	Teamwork Optimization Algorithm (TOA)	2021
113	Thieves And Police Algorithm (TPA)	2021
114	Unconscious Search (US)	2012
115	War Strategy Optimization Algorithm (WSO)	2022
116	Weighted-Leader Search (WLS)	2023
117	Wisdom of Artificial Crowds (WoAC)	2011
118	Zombie Survival Optimization (ZSO)	2012
	Sports metaheuristics	
119	Athletic Run Based Optimization (ARBO)	2021
120	Battle Royale Optimization (BRO)	2021
121	Billards-Inspired Optimization Algorithm (BIOA)	2020
122	Boxing Match Algorithm (BMA)	2022
123	Chaos Game Optimization (CGO)	2021
124	Darts Game Optimizer (DGO)	2020
125	Dice Game Optimizer (DGO)	2019
126	Football Game Algorithm (FGA)	2016
127	Football Optimization Algorithm (FOA)	2012
128	Golden Ball Algorithm (GBA)	2014
129	Golf Optimization Algorithm (GOA)	2023
130	Hide Objects Game Optimization (HOGO)	2020
131	Jigsaw Puzzle Algorithm (JPA)	2013
132	Kho-Kho Optimization (KKO)	2020
133	League Championship Algorithm (LCA)	2014
134	Ludo Game-based Swarm Intelligence (LGSI)	2019
135	Most Valuable Player Algorithm (MVPA)	2020
136	Oriented Search Algorithm (OSA)	2019
137	Puzzle Optimization Algorithm (POA)	2022
138	Quad Tournament Optimizer (QTO)	2023
139	Ring Toss Game-Based Optimization (RTGBO)	2021
140	Shell Game Optimization (SGO)	2020
141	Soccer Game Optimization (SGO)	2017
142	Soccer League Competition Algorithm (SLC)	2014
143	Squid Game Optimizer (SGO)	2023
144	Team Game Algorithm (TGA)	2018
145	Tiki-Taka Algorithm (TTA)	2021
146	Tug of War Optimization (TWO)	2016
147	Volleyball Premier League Algorithm (VPL)	2018
148	Wingsuit Flying Search (WFS)	2020
149	World Cup Optimization (WCO)	2016
	Maths metaheuristics	
150	Arithmetic Optimization Algorithm (AOA)	2021
151	Base Optimization Algorithm (BOA)	2012
152	Deterministic Oscillatory Search (DOS)	2017
153	Exponential Distribution Optimizer (EDO)	2023
154	Fractal-based Algorithm (FBA)	1996
155	Generalized Normal Distribution Optimization (GNDO)	2020
156	Geometric Octal Zones Distance Estimation (GOZDE)	2022
157	Golden Sine Algorithm (Gold-SA)	2017
158	Gradient-based Optimizer (GBO)	2020
159	K-means Optimizer (KO)	2022
160	Matheuristics	2009

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161	RUNge kutta algorithm(RUN)	2021
162	Simulated Kalman Filter Algorithm (SKF)	2016
163	Sine Cosine Algorithm (SCA)	2016
164	Spiral Dynamics Inspired Optimization (SDIO)	2011
165	Stochastic Fractal Search (SFS)	2015
166	Subtraction-Average-Based Optimizer (SABO)	2023
167	Tangent Search Algorithm (TSA)	2022
168	Weighted Vertices Optimizer (WVO)	2018
	Physics-Chemistry metaheuristics	
169	Al-Biruni Earth Radius (BER)	2023
170	Archimedes Optimization Algorithm (AOA)	2021
171	Artificial Atom Algorithm (AAA)	2017
172	Artificial Chemical Process (ACP)	2005
173	Artificial Chemical Reaction Optimization Algorithm (ACROA)	2011
174	Artificial Ecosystem-Based Optimization (AEO)	2020
175	Artificial Electric Field Algorithm(AEFA)	2019
176	Artificial Physics Optimization (AEFA)	2009
177	Artificial Raindrop Algorithm (ARD)	2015
178	Artificial Reaction Algorithm (ARA)	2011
179	Atmosphere Clouds Model Optimization (ACMO)	2012
180	Atom Search Optimization (ASO)	2019
181	Atom Stabilization Algorithm (ASA)	2016
182	Atomic Orbital Search (AOS)	2021
183	Balancing Composite Motion Optimization (BCMO)	2020
184	Big Bang-Big Crunch (BB-BC)	2012
185	Black Hole (BH)	2013
186	Black Hole Mechanics Optimization (BHMO)	2020
187	Car Tracking Optimization (CTO)	2018
188	Central Force Optimization (CFO)	2007
189	Charged System Search (CSS)	2010
190	Chemical Reaction Algorithm (CRA)	2013
191	Chemical Reaction Optimization (CRO)	2010
192	Chemotherapy Science Algorithm (CSA)	2017
193	Cloud Particles Differential Evolution Algorithm (CPDE)	2015
194	Colliding Bodies Optimization (CBO)	2014
195	Crystal Energy Optimization Algorithm (CEO)	2016
196	Crystal Structure Algorithm (CryStAI)	2021
197	Curved Space Optimization (CSO)	2012
198	Dark-Matter Search Optimizer (DSO)	2023
199	Drone Squadron Optimization (DSO)	2018
200	Droplet Optimization Algorithm (DOA)	2018
201	Drops Contact Optimization (DCO)	2016
202	Drops on Surface Optimization (DSO)	2022
203	Electrical Search Algorithm (ESA)	2022
204	Electromagnetic Field Optimization (EFO)	2016
205	Electro-Magnetism Optimization (EMO)	2012
206	Electromagnetism-Like Mechanism Optimization (EMO)	2003
207	Electron Radar Search (ERSA)	2020
208	Equilibrium Optimizer (EO)	2020
209	Extremal Optimization (EO)	1999
210	Fick's Law Optimization (FLA)	2023
211	Flow Direction Algorithm (FDA)	2021
212	Flow Regime Algorithm (FRA)	2019
213	Galactic Swarm Optimization (GSO)	2016
214	Galaxy-Based Search Algorithm (GBSA)	2011
215	Gas Molecules Dispersion (GMD)	2023

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216	Gases Brownian Motion Optimization (GBMO)	2013
217	General Relativity Search Algorithm (GRSA)	2015
218	Gravitation Field Algorithm (GFA)	2010
219	Gravitational Clustering Algorithm (GCA)	1999
220	Gravitational Emulation Local Search (GELS)	2009
221	Gravitational Interactions Optimization (GIO)	2011
222	Gravitational Search Algorithm (GSA)	2009
223	Grenade Explosion Algorithm (GEA)	2010
224	Heat Transfer Search (HTS)	2015
225	Henry Gas Solubility Optimization (HGSO)	2019
226	Hurricane Based Optimization Algorithm (HO)	2014
227	Hydrological Cycle Algorithm (HCA)	2017
228	Hysteretic Optimization (HO)	2001
229	Integrated Radiation Optimization (IRO)	2007
230	Intelligent Water Drops (IWD)	2007
231	Ions Motion Optimization (IMO)	2015
232	Kepler optimization algorithm (KOA)	2023
233	Kinetic Gas Molecules Optimization (KGMO)	2014
234	Lens Law Optimization (LLO)	2023
235	Lichtenberg Algorithm (LA)	2021
236	Light Ray Optimization Algorithm (LRO)	2009
237	Lightning Attachment Procedure Optimization (LAPO)	2017
238	Lightning Search Algorithm (LSA)	2015
239	Limited Memory Q-BFGS algorithm (LMQA)	2021
240	Magnetic Optimization Algorithm (MOA)	2008
241	Material Generation Algorithm (MGA)	2021
242	Mine Blast Algorithm (MBA)	2012
243	Momentum Search Algorithm (MSA)	2020
244	Multi-verse Optimizer (MVO)	2016
245	Newton Metaheuristic Algorithm (NMA)	2020
246	Nuclear Reaction Optimization (NRO)	2019
247	Optics Inspired Optimization (OIO)	2015
248	Particle Collision Algorithm (PCA)	2005
249	Passing Vehicle Search (PVS)	2016
250	Photon Search Algorithm (PSA)	2020
251	Photosynthetic Learning Algorithm (PLA)	1998
252	Plasma Generation Optimization (PGO)	2020
253	PopMusic Algorithm (PopMusic)	2019
254	Projectiles Optimization (PRO)	2020
255	Quantum Superposition Algorithm (QSA)	2015
256	Quantum-inspired Gravitational Search Algorithm (QIGSA)	2014
257	Radial Movement Optimization (RMO)	2014
258	Rain Optimization Algorithm (ROA)	2020
259	Rain Water Algorithm (RWA)	2017
260	Raindrop Algorithm (RDA)	2013
261	Rainfall Optimization (RO)	2017
262	Ray Optimization (RO)	2012
263	Rime Optimization Algorithm (RIME)	2023
264	River Formation Dynamics (RFD)	2007
265	SaMW	2021
266	Self-Driven Particles (SPP)	1995
267	Self-Propelled Particles (SPP)	2017
268	Simulated Annealing (SA)	1983
269	Simulated Raindrop (SRD)	2014
270	Small World Optimization Algorithm (SWOA)	2006
271	Snow Ablation Optimizer (SAO)	2023

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272	Solar System Algorithm (SSA)	2020
273	Sonar Inspired Optimization (SIO)	2017
274	Space Gravitational Algorithm (SGA)	2005
275	Special Relativity Search (SRS)	2022
276	Spring Search Algorithm (SSA)	2017
277	States Matter Search (SMS)	2014
278	Stochastic Diffusion Search (SDS)	1999
279	String Theory Algorithm (STA)	2022
280	Supernova Optimizer (SO)	2018
281	Synergistic Fibroblast Optimization (SFO)	2017
282	Thermal Exchange Optimization (TEO)	2017
283	Transient Search Optimization Algorithm (TSO)	2020
284	Turbulent Flow of Water-based Optimization (TFWO)	2020
285	Vapor-Liquid Equilibrium (VLE)	2020
286	Vibrating Particles System (VPS)	2017
287	Volcano Eruption Algorithm (VEA)	2021
288	Vortex Search (VS)	2015
289	Water Cycle Algorithm (WCA)	2012
290	Water Evaporation Optimization (WEO)	2016
291	Water Flow Algorithm	2011
292	Water Flow Optimizer (WFO)	2022
293	Water Flow-Like Algorithm (WFA)	2007
294	Water Optimization Algorithm (WOA)	2022
295	Water Wave Optimization (WWO)	2015
296	WeIghted meaN oF vectOrs (INFO)	2022
297	Weighted Superposition Attraction (WSA)	2017
298	Wind Driven Optimization (WDO)	2010
299	Yin-Yang-pair Optimization (YYO)	2016
300	Young's Double-Slit Experiment (YDSE)	2023
	Evolution metaheuristics	
301	Artificial Immune System (AIS)	1995
302	Artificial Infectious Disease Optimization (AIDO)	2016
303	Asexual Reproduction Optimization (ARO)	2010
304	Backtracking Search Optimization (BSA)	2013
305	Bacterial Evolutionary Algorithm (BEA)	1996
306	Bean Optimization Algorithm (BOA)	2010
307	Bio-breeding Intelligent Swarm (BIS)	2020
308	Biogeography Based Optimization (BBO)	2008
309	Bird Mating Optimization (BMO)	2014
310	Bull Optimization Algorithm (BOA)	2015
311	Clonal Selection Algorithm (CSA)	2000
312	Coevolutionary Algorithm (CA)	1995
313	Coral Reefs Optimization (CRO)	2014
314	Covariance Matrix Adaptation–Evolution Strategy (CMA-ES)	2003
315	Dendritic Cells Algorithm (DCA)	2005
316	Differential Evolution (DE)	2009
317	Differential Search Algorithm (DSA)	2012
318	Earthworm Optimization Algorithm (EOA)	2018
319	Ecogeography-Based Optimization (EBO)	2014
320	Eco-Inspired Evolutionary Algorithm (EEA)	2011
321	Evolution Strategies (ES)	1973
322	Evolutionary Programming (EP)	1965
323	Gene Expression (GE)	2002
324	Gene Expression Programming (GEP)	2001
325	Genetic Algorithms (GA)	1973
326	Genetic Programming (GP)	1994

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327	Germinal Center Artificial Immune System (GCAIS)	2022
328	Gradient Evolution Algorithm (GEA)	2015
329	Grey Prediction Evolution Algorithm (GPEA)	
330	Hyper-Spherical Search (HSS)	2014
331	Immune-Inspired Computational Intelligence (ICI)	2008
332	Kaizen Programming (KP)	2014
333	Linear Prediction Evolution Algorithm (LPE)	2021
334	Marriage In Honey Bees Optimization (MHBO)	2007
335	Memetic Algorithms (MA)	1989
336	Multivariable Grey Prediction Evolution Algorithm (MGPEA)	2020
337	Queen-Bee Evolution (QBE)	2003
338	Self-Organizing Migrating Algorithm (SOMA)	2016
339	Sheep Flock Heredity Model (SFHM)	1999
340	Shuffled Complex Evolution (SCE)	1993
341	Stem Cells Algorithm (SCA)	2012
342	SuperBug Algorithm (SuA)	2012
343	Swine Influenza Models-Based Optimization (SIMBO)	2013
344	Variable Mesh Optimization (VMO)	2012
345	Virulence Optimization Algorithm (VOA)	2016
	Flying swarm metaheuristics	
346	Andean Condor Algorithm (ACA)	2019
347	Aquila Optimizer (AO)	2021
348	Artificial Bee Colony (ABC)	2007
349	Artificial Beehive Algorithm (ABHA)	2009
350	Artificial Butterfly Optimization (ABO)	2017
351	Artificial Feeding Birds (AFB)	2018
352	Artificial Hummingbird Algorithm (AHA)	2022
353	Artificial Transgender Longicorn Algorithm (ATLA)	2020
354	Bald Eagle Search (BES)	2020
355	Bat Inspired Algorithm (BIA)	2010
356	Bat Intelligence (BI)	2012
357	Bee Colony Optimization (BCO)	1988
358	Bee Colony-Inspired Algorithm (BCIA)	2009
359	Bee Swarm Optimization (BSO)	2010
360	Bee System (BS)	1998
361	BeeHive Algorithm (BHA)	2004
362	Bees Algorithm (BA)	2006
363	Bees Life Algorithm (BLA)	2012
364	Bees Swarm Optimization Algorithm (BSOA)	2010
365	Beetle Swarm Antennae Search (BSAS)	2018
366	Beetle Swarm Optimization Algorithm (BSOA)	2020
367	Bioluminescent Swarm Optimization (BSO)	2011
368	Bird Swarm Algorithm (BSA)	2016
369	Bumble Bees Mating Optimization (BBMO)	2009
370	Butterfly Optimizer (BO)	2015
371	Buzzard Optimization Algorithm (BOA)	2019
372	Chaotic Dragonfly Algorithm (CDA)	2019
373	Co-Operation Of Biology Related Algorithm (COBRA)	2013
374	Crow Search Algorithm (CSA)	2016
375	Cuckoo Search (CS)	2010
376	Cyclical Parthenogenesis (CP)	2017
377	Dragonfly Algorithm (DA)	2016
378	Dynamic Virtual Bats Algorithm (DVBA)	2016
379	Eagle Strategy (ES)	2010
380	Egyptian Vulture Optimization Algorithm (EV)	2013
381	Falcon Optimization Algorithm (FOA)	2019

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382	Fire Hawk Optimizer (FHO)	2022
383	Firefly Algorithm (FA)	2009
384	Fitness Dependent Optimizer (FDO)	2019
385	Flock by Leader (FL)	2012
386	Flocking Base Algorithms (FBA)	2006
387	Fly Optimization Algorithm (FOA)	2010
388	Flying Squirrel Optimizer (FSO)	2019
389	Fruit Fly Optimization Algorithm (FOA)	2012
390	Glowworm Swarm Optimization (GSO)	2009
391	Golden Eagle Optimizer (GEO)	2021
392	Goose Team Optimization (GTO)	2008
393	Harris Hawks Optimization Algorithm (HHO)	2019
394	Hitchcock Bird-Inspired Algorithm (HBIA	2018
395	Honeybee Social Foraging (HSF)	2007
396	Honey-Bees Mating Optimization (HBMO)	2006
397	Hoopoe Heuristic Optimization (HHO)	1989
398	Jackson's Widowbird Mating Optimization (JWMO)	2020
399	Mantis Search Algorithm (MSA)	2023
400	Mayfly Optimization Algorithm (MOA)	2020
401	Migrating Birds Optimization (MBF)	2012
402	Modified Cuckoo Search (MCS)	2011
403	Monarch Butterfly Optimization (MBO)	2016
404	Mosquito Flying Algorithm (MFO)	2016
405	Moth Flame Optimization Algorithm (MFO)	2015
406	Moth Swarm Algorithm (MSA)	2017
407	Mox Optimization Algorithm (MOX)	2011
408	Murmuration-flight-based Dispersive Optimization (MDO)	2023
409	New Caledonian Crow Learning Algorithm (NCCLA)	2020
410	Northern Goshawk Optimization (NGO)	2021
411	Nutcracker Optimization Algorithm (NOA)	2023
412	OptBees (OB)	2013
413	Particle Swarm Optimization (PSO)	1995
414	Pigeon Inspired Optimization (PIO)	2014
415	Quantum-based Avian Navigation Optimizer (QANA)	2021
416	Raven Roosting Algorithm (RRO)	2019
417	Regular Butterfly Optimization Algorithm (RBOA)	2019
418	Sandpiper Optimization Algorithm (SOA)	2020
419	Satin Bowerbird Optimizer (SBO)	2017
420	Seagull Optimization Algorithm (SOA)	2019
421	See-See Partridge Chicks Optimization (SSPCO)	2016
422	Seven-Spot Ladybird Optimization (LBO)	2013
423	Shuffled Multi-Swarm Micro-Migrating Birds Optimization (SM2-MBO)	2016
424	Simulated Bee Colony (SBC)	2009
425	Snap-Drift Cuckoo Search (SDCS)	2017
426	Sooty Tern Optimization Algorithm (STOA)	2019
427	Sparrow Search Algorithm (SSA)	2020
428	Spider Wasp Optimization (SWO)	2023
429	Starling Murmuration Optimizer (SMO)	2022
430	Swallow Swarm Optimization (SSO)	2013
431	Swarm Inspired Projection (SIP)	2009
432	Virtual Ants Algorithm (VAA)	2006
433	Virtual Bees Algorithm (VBA)	2005
434	Wasp Swarm Optimization (WSA)	2005
435	Woodpecker Mating Algorithm (WMA)	2020
	Aquatic swarm metaheuristics	
436	Archerfish Hunting Optimizer (AHO)	2022

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437	Artificial Fish Swarm Algorithm (AFSA)	2002
438	Artificial Jellyfish Search (JS)	2021
439	Barnacles Mating Optimizer (BMO)	2018
440	Beluga Whale Optimization (BWO)	2022
441	Catfish Optimization Algorithm (CAO)	2008
442	Circular Structures of Puffer Fish Algorithm (CSOPF)	2018
443	Coot Optimization Algorithm (COT)	2021
444	Cuttlefish Algorithm (CFA)	2013
445	Dolphin Echolocation (DE)	2013
446	Dolphin Partner Optimization (DPO)	2009
447	Electric Fish Optimization (EFO)	2020
448	Emperor Penguins Colony (EPC)	2019
449	Fish School Search (FSS)	2008
450	Fish Swarm Algorithm (FSA)	2002
451	Giant Trevally Optimizer (GTO)	2022
452	Group Escape Behavior (GEB)	2011
453	Hammerhead Shark Optimization (HSO)	2019
454	Hermit Crab Shell Exchange Algorithm (HCSE)	2022
455	Keshtel Algorithm (KA)	2019
456	Killer Whale Algorithm (KWA)	2017
457	Krill Herd (KH)	2012
458	Leopard Seal Optimization (LSO)	2023
459	Locust Swarms Optimization (LSO)	2009
460	Manta Ray Foraging (MRFO)	2020
461	Marine Predators Algorithm (MOA)	2020
462	Mouth Brooding Fish Algorithm (MBF)	2018
463	Mussels Wandering Optimization (MWO)	2013
464	Orca Optimization Algorithm (OOA)	2020
465	Orca Predation Algorithm (OPA)	2022
466	Pelican Optimization Algorithm (POA)	2022
467	Penguins Search Optimization Algorithm (PeSOA)	2013
468	Pufferfish Optimization Algorithm (PFOA)	2022
469	Remora Optimization Algorithm (ROA)	2021
470	Reptile Search Algorithm (RSA)	2022
471	Ring Seal Search (RSS)	2016
472	Sailfish Optimizer (SFO)	2019
473	Salp Swarm algorithm (SSA)	2017
474	Sea Lion Optimization (SLnO)	2019
475	Sea-Horse Optimizer (SHO)	2022
476	Shark Search Algorithm (SA)	1998
477	Shark Smell Optimization (SSO	2016
478	Skip Salp Swarm Algorithm (SSSA)	2022
479	Sperm Whale Algorithm (SWA)	2016
480	The Great Salmon Run Algorithm (TGSR)	2012
481	Tuna Swarm Optimization (TSO)	2021
482	Tunicate Swarm Algorithm (TSA)	2020
483	Victoria Amazonica Plant (VAP)	2023
484	Walrus Optimization Algorithm (WaOA)	2023
485	Water Strider Algorithm (WSA)	2020
486	Whale Optimization Algorithm (WOA)	2016
487	White Shark Optimizer (WSO)	2022
488	Yellow Saddle Goatfish Algorithm (YSGA)	2018
	Micro swarm metaheuristics	
489	Artificial Algae Algorithm (AAA)	2015
490	Bacteria for Distributed Optimization (BDO)	2002
491	Bacterial Chemotaxis Optimization (BCO)	2002

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492	Bacterial Colony Optimization (BCO)	2012
493	Bacterial Foraging Optimization (BFOA)	2009
494	Bacterial Swarming Algorithm (BSA)	2007
495	Bacterial-GA Foraging (BGAF)	2007
496	Biomimicry of Social Foraging (BSF)	2002
497	Coronavirus Herd Immunity (CHIO)	2021
498	Coronavirus Metamorphosis Optimization Algorithm (CMOA)	2023
499	Coronavirus Optimization Algorithm (CvOA)	2020
500	COVID-19 Optimizer Algorithm (CVA)	2020
501	Ebola Optimization Search Algorithm (EOSA)	2022
502	Fast Bacterial Swarming Algorithm (FBSA)	2008
503	Invasive Tumor Growth Optimization (ITGO)	2015
504	Liver Cancer Algorithm (LCA)	2023
505	Magnetotactic Bacteria Optimization (MBO)	2013
506	Physarum Optimization (PO)	2015
507	Slime Mould Algorithm (SMA)	2020
508	Sperm Swarm Optimization Algorithm (SSOP)	2018
509	Viral Systems Optimization (VSO)	2008
510	Virus Colony Search (VCS)	2016
511	Virus Optimization Algorithm (VOA)	2009
512	Wasp Colonies Algorithm (WCA)	2005
513	Worm Optimization (WO)	2014
	Plants metaheuristics	
514	Artificial Flora Optimization Algorithm (AF)	2018
515	Artificial Photosynthesis and Phototropism Mechanism (APPM)	2012
516	Artificial Plants Optimization Algorithm (APO)	2011
517	Brunsvigia Optimization Algorithm (BVOA)	2018
518	Dandelion Optimizer (DO)	2022
519	Farmland Fertility (FF)	2018
520	Flower Pollination Algorithm (FPA)	2012
521	Forest Optimization Algorithm (FOA)	2014
522	Grass Fibrous Root Algorithm (GRA)	2017
523	Hazelnut Tree Search (HST)	2021
524	Invasive Weed Optimization (IWO)	2006
525	Lotus Effect Algorithm (LEA)	2023
526	Mushroom Reproduction Optimization (MRO)	2018
527	Natural Forest Regeneration Algorithm (NFR)	2016
528	Orchard Algorithm (OA)	2023
529	Paddy Field Algorithm (PFA)	2009
530	Plant Growth Optimization (PGO)	2017
531	Plant Propagation Algorithm (PPA)	2014
532	Plum Tree Algorithm (PTA)	2023
533	Poplar Optimization Algorithm (POA	2022
534	Root Growth Optimizer (RGO)	2015
535	Root Tree Algorithm (RTO)	2016
536	Runner Root Algorithm (RRA)	2015
537	Saplings Growing Up Algorithm (SGA)	2006
538	Seasons Optimization (SO)	2022
539	Self-Defense Mechanism of the Plants Algorithm (SDMA)	2018
540	Smart Flower Optimization Algorithm (SFOA)	2021
541	Strawberry Algorithm (SA)	2014
542	Sun Flower Optimization Algorithm (SFOA)	2019
543	Tree Growth Algorithm (TGA)	2018
544	Tree Optimization Algorithm (TOA)	2022
545	Tree Physiology Optimization (TPO)	2013
546	Tree Seed Algorithm (TSA)	2022

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547	Trees Social Relations Algorithm (TSR)	2022
548	Victoria Amazonica Optimization (VAO)	2023
549	Waterwheel Plant technique Algorithm (WWPA)	2023
550	Weed Colonization Optimization (WCO)	2006
	Terrestrial swarm metaheuristics	
551	Prairie Dog Optimization (PDO)	2023
552	African Buffalo Optimization (ABO)	2016
553	African Vultures Optimization Algorithm (AVOA)	2021
554	African Wild Dog Algorithm (AWDA)	2015
555	American Zebra Optimization Algorithm (AZOA)	2023
556	Ant Colony Optimization (ACO)	1996
557	Ant Path Integration (API)	2023
558	Aphid Optimization Algorithm (AOA)	2022
559	Artificial Gorilla Troops (AGT)	2021
560	Artificial Lizard Search Optimization (ALSO)	2021
561	Artificial Rabbits Optimizer (ARO)	2022
562	Bear Smell Search Algorithm (BSSA)	2020
563	Bison Behavior Algorithm (BBA)	2019
564	Bison Colony Algorithm (BBA)	2019
565	Black Widow Optimization Algorithm (BWO)	2020
566	Blind, Naked Mole-Rats Algorithms (BNMR)	2012
567	Blue Monkey Algorithm (BMA)	2019
568	Bonobo Optimizer (BO)	2019
569	Border Collie Optimization (BCO)	2020
570	Camel Algorithm (CA)	2016
571	Camel Herds Algorithm (CHA)	2017
572	Cat Hunting Optimization Algorithm (CHO)	2023
573	Cat Swarm Optimization (CSO)	2006
574	Chameleon Swarm Algorithm (CSA)	2021
575	Cheetah Based Algorithms (CBA)	2018
576	Cheetah Chase Algorithm (CCA)	2018
577	Cheetah Optimizer (CO)	2022
578	Chicken Swarm Optimization (CSO)	2014
579	Chimp Optimization Algorithm (ChOA)	2020
580	Coati Optimization Algorithm (COA)	2023
581	Cockroach Swarm Optimization (CSO)	2014
582	Coyote Optimization Algorithm (COA)	2018
583	Cricket Behavior-Based Algorithm (CBBE)	2016
584	Cricket Chirping Algorithm (CCA	2018
585	Cultural Coyote Optimization Algorithm (CCOA)	2019
586	Deer Hunting Optimization Algorithm (DHOA)	2019
587	Dingo Optimizer (DOX)	2021
588	Donkey Theorem Optimization (DTO	2019
589	Dung Beetle Optimizer (DBO)	2023
590	Dwarf Mongoose Optimization (DMO)	2022
591	Elephant Clan Optimization (ECO)	2021
592	Elephant Herding Optimization (EHO)	2016
593	Elephant Search Algorithm (ESA)	2015
594	Fast Jaguar Algorithm (FJA)	2021
595	Frog Call Inspired Algorithm (FCA)	2004
596	FrogSim	2014
597	Gazelle Optimization Algorithm (GOA)	2022
598	Grasshopper Optimization Algorithm (GOA)	2017
599	Green Anaconda Optimization (GAO)	2023
600	Grey Wolf Optimizer (GWO)	2014
601	Honey Badger Algorithm (HBA)	2022

Continued on next page

Table 2 continued

602	Horse Herd Optimization Algorithm (HOA)	2021
603	Hunter-prey Optimization (HPO)	2022
604	Hunting Search Algorithm (HuS)	2014
605	Jaguar Algorithm (JA)	2016
606	Japanese Tree Frogs Calling Algorithm (JTFC)	2012
607	Komodo Mlipir Algorithm (KMA)	2022
608	Laying Chicken Algorithm (LCA)	2017
609	Lemur Optimizer (LO)	2022
610	Lion Algorithm (LA)	2012
611	Lion Optimization Algorithm (LOA)	2016
612	Lion Pride Optimization Algorithm (LPOA)	2018
613	Lion Pride Optimizer (LPO)	2012
614	Meerkats Inspired Algorithm (MIA)	2018
615	Mobility Aware-Termite (MA-Termite)	2013
616	Monkey King Evolutionary (MKE)	2016
617	Monkey Search (MS)	2007
618	Moth Search Algorithm (MSA)	2018
619	Naked Mole-Rat (NMR)	2019
620	Pity Beetle Algorithm (PBA)	2018
621	Polar Bear Optimization (PBO)	2017
622	Porcellio Scaber Algorithm (PSA)	2017
623	Predator-Prey Optimization (PPO)	2022
624	Prey-Predator Algorithm(PPA)	2015
625	Raccoon Optimization Algorithm (ROA)	2018
626	Red Colobuses Monkey (RCM)	2021
627	Red Deer Algorithm (RDA)	2016
628	Red Fox Optimization (RFO)	2021
629	Red Panda Optimization (RPO)	2023
630	Rhino Herd Behavior (RBH)	2018
631	Rhinoceros Search Algorithm (RSA)	2017
632	Roach Infestation Problem (RIO)	2008
633	Sand Cat Swarm Optimization (SCSO)	2023
634	Shuffled Frog-Leaping algorithm (SFLA)	2006
635	Snake Optimizer (SO)	2022
636	Social Spider Algorithm (SSO)	2015
637	Spider Monkey Optimization (SMO)	2014
638	Spotted Hyena Optimizer (SHO)	2017
639	Squirrel Search Algorithm (SSA)	2019
640	Termite Colony Optimization (TCO)	2010
641	Termite Hill algorithm (TA)	2012
642	Termite Life Cycle Optimizer (TLCO)	2023
643	Termite Life Cycle Optimizer (TLO)	2023
644	Tyrannosaurus (T-Rex) Optimization Algorithm (TROA)	2023
645	Wild Horse Optimizer (WHO)	2022
646	Wild Mice Colony Algorithm (WMC)	2019
647	Wolf Colony Algorithm (WCA)	2011
648	Wolf Pack Search (WPS)	2007
649	Wolf Search Algorithm (WSA)	2012
650	Xerus Optimization Algorithm (XOA)	2019
	Music metaheuristics	
651	Harmony Elements Algorithm (HEA)	2008
652	Harmony Search (HS)	2001
653	Melody Search (MS)	2011
654	Method of Musical Composition (MMC)	2014

3.4 Research objective 3: Development trend and percentage representation of metaheuristics

Over the expansive timeline from 1965 to August 2023, the world of metaheuristics has undergone a remarkable transformation, introducing 654 distinct metaheuristics. These innovative approaches take inspiration from various classes of metaphorical behaviours in the field.Figure 6 illustrates how these metaheuristics have evolved.

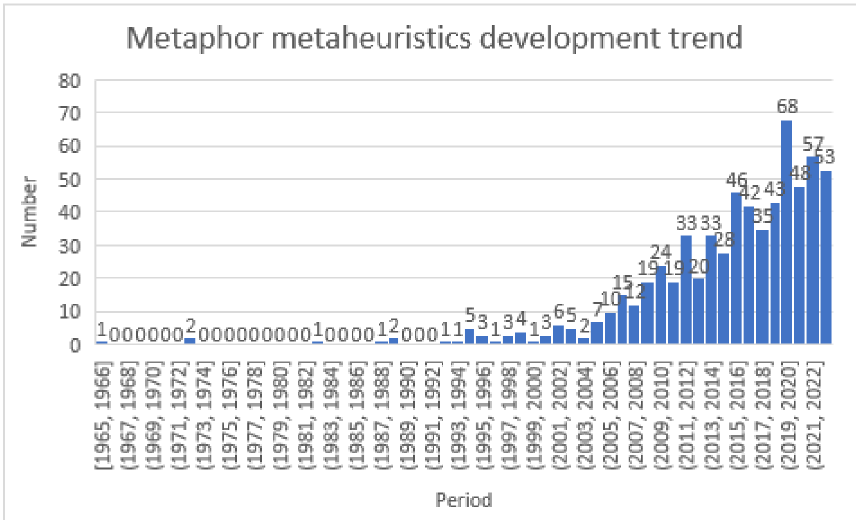

Fig 6. Metaphor metaheuristics development trend

The trend keeps inclining over the years. The peak year for such introductions was 2020, with a remarkable 68 new metaheuristics released. This was followed closely by 2022, in which 57 new metaheuristics were introduced. As of August 2023, there have been 53 new metaheuristics introduced, indicating that the field continues to evolve rapidly. However, it's worth noting that during some years in the early stages of metaheuristic development, between 1965 and 1992, the field experienced periods of stagnation and progress was limited to only one or two new approaches per year. These were relatively quiet and uneventful phases. Then, between 1992 and 2005, there was a gradual inclination with the numbers eventually reaching a peak of seven per year.

A pivotal moment in the field's history was observed in 2006 when the idea of metaheuristics gained significant traction among researchers. This marked a turning point as 10 new metaheuristics burst onto the scene, heralding a new era of accelerated creativity and exploration in this field. These algorithms include the flocking base algorithm (FBA), honey-bees mating optimization (HBMO), virtual ants algorithm (VAA), small world optimization algorithm (SWOA), invasive weed optimization (IWO), saplings growing up algorithm (SGA), weed colonization optimization (WCO), shuffled frog-leaping algorithm (SFLA), cat swarm optimization (CSO), and bees algorithm (BA).

Emphasizing the outburst, fifteen algorithms emerged in 2007 spread over the metaphoric schemes. Notably include the wolf pack search (WPS), monkey search (MS), water flow-like algorithm (WFA), river formation dynamics (RFD), intelligent water drops (IWD), integrated radiation optimization (IRO), central force optimization (CFO), bacterial-GA foraging (BGAF), bacterial swarming algorithm (BSA), seeker optimization algorithm (SOA), imperialist competitive algorithm (ICA), honeybee social foraging (HSF), artificial bee colony (ABC), marriage in honey bees optimization (MHBO), and human evolutionary model (HEM).

Figure 7 presents the percentage distribution of the 654 metaheuristics according to their metaphor classifications. At the forefront, "physics-chemistry" represents the dominant force, having a substantial 20%. This is followed closely by the "human" classification at 18%, securing the second-highest position, with "terrestrial" ranking third at 15%. As we explore further, "flying animals" take up 14%, while "evolutionary" captures 7% of the landscape. "Plants" contribute 6%, "sports" bring in 5%, "microorganisms" make their mark at 4%, and the mathematical realm accounts for 3%. Surprisingly, "Music" has no representation.

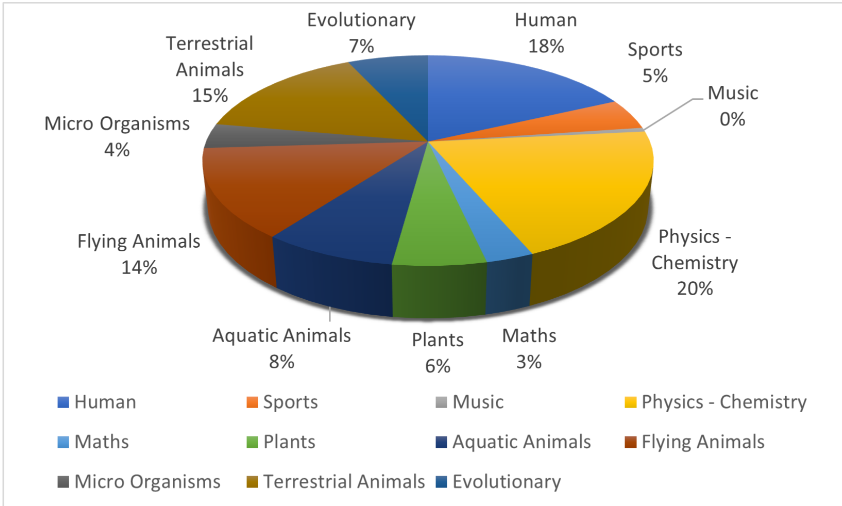

Fig 7. Percentage of various metaphor metaheuristics contributed from 1965 to August 2023

4 Conclusion

Through this study, we investigated metaheuristic classification and presented a comprehensive classification scheme. We classified an exhaustive list of 654 metaheuristics proposed from 1965 to August 2023 into various metaphor groups and analyzed their development, evolution, and percentage-wise representation. Our research indicates a significant evolution in metaheuristic development, with notable peaks in 2020 (68 new metaheuristics) and 2022 (57 new metaheuristics) and continued growth in 2023 with 53 new introductions. Early stages between 1965 and 1992 experienced stagnation with only one or two new approaches annually, while a pivotal increase began in 2006 with 10 new metaheuristics, marking the start of accelerated innovation. Among the 654 metaheuristics, "physics-chemistry" leads with 20%, followed by "human" at 18%, "terrestrial" at 15%, and "flying animals" at 14%, with other groups trailing. Notably, "music" is absent. Additionally, recent advancements have employed several techniques to enhance the performance of standard metaheuristics. Future research could focus on identifying and classifying various variants of classical metaheuristics, including techniques such as augmented lagrangian search, fuzzy logic, chaotic mapping, binary encoding, quantization, and hybridization.'

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