A Systematic Review of Metaheuristic Algorithms in Human Activity Recognition: Applications, Trends, and Challenges

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***Abstract*—Metaheuristic algorithms have emerged as promising techniques for optimizing human activity recognition (HAR) systems. This systematic review examines the application of these algorithms in HAR by analyzing relevant literature published between 2019 and 2024. A comprehensive search across multiple databases yielded 27 studies that met the inclusion criteria. The analysis revealed that Genetic Algorithms (GA) exhibit classification accuracy rates ranging from 88.25% to 96.00% in activity recognition and up to 90.63% in localization tasks. Notably, Oppositional and Chaos Particle Swarm Optimization (OCPSO) combined with MI-1DCNN significantly improves detection accuracy, demonstrating a 2.82% improvement over standard PSO with Support Vector Machine (SVM) as classifier approaches. Our analysis highlights a growing trend toward hybrid metaheuristic approaches that enhance feature selection and classifier optimization. However, challenges related to computational cost and scalability persist, underscoring key areas for future research. These findings emphasize the potential of metaheuristic algorithms to significantly advance HAR. Future studies should explore the development of more computationally efficient hybrid models and the integration of metaheuristic optimization with deep learning architectures to enhance system robustness and adaptability.**

***Keywords*—Metaheuristic algorithm; human activity recognition; systematic review; application; trend; challenge; literature**

I. Introduction

Human Activity Recognition (HAR) is a crucial field that extends its influence across diverse domains, including healthcare, sports, and security, by employing its ability to classify human body movements and gestures based on sensor data [1], [2]. The incorporation of HAR within these domains has initiated significant transformative possibilities, reshaping patient care, enhancing athletic training, and strengthening security protocols [3]. Nevertheless, the effectiveness of HAR relies heavily on their ability to process complex, multidimensional data accurately. To address this complexity, metaheuristic algorithms have proven to be invaluable resources, drawing inspiration from natural phenomena such as evolution and swarm behaviors [4], [5]. Metaheuristic algorithms are powerful optimization strategies designed to tackle complex problems that traditional methods struggle to solve. They allow for the exploration of extensive search spaces to identify the best possible solutions to various issues [6]. The development of these algorithms has taken place over several decades and draws inspiration from natural systems, leading to a range of innovative optimization techniques. We believe that metaheuristic algorithms will continue to be instrumental in driving advancements in new technologies and applications, proving to be invaluable tools for addressing intricate optimization challenges across different fields.

In recent years, HAR technology has revolutionized healthcare monitoring through sophisticated patient movement analysis and personalized rehabilitation programs, while enabling early detection of health issues through non-invasive monitoring methods that provide real-time treatment efficacy feedback. This innovative technology extends its capabilities into sports applications, where it facilitates precise analysis of athletic performance through comprehensive movement and strain monitoring, and further demonstrates its versatility in security systems by identifying unauthorized access and unusual behavioral patterns. The integration of HAR systems across these diverse domains exemplifies its fundamental role in advancing human-centric technological solutions that enhance monitoring, analysis, and decision-making processes in critical sectors.

Despite the advancements in HAR technology, challenges persist, particularly when it comes to processing large and unstructured datasets. This is where metaheuristic algorithms come into play. They offer a promising solution by optimizing the recognition process through efficient exploration of various solution spaces. However, integrating these algorithms with HAR presents unique challenges, as they must be capable of identifying meaningful patterns without falling into the trap of overfitting [1].

Metaheuristic algorithms tackle several specific challenges within HAR. One significant issue is the high dimensionality of sensor data, which can overwhelm traditional algorithms. By ensuring robust feature selection, these algorithms enhance classification accuracy while reducing computational burdens. They also adapt to variations in human activities and device usage, adding complexity to data interpretation. Furthermore, advancements in sensor technologies such as depth sensors and wearable devices allow metaheuristic algorithms to leverage richer data for more nuanced activity inferences [4].

The broader implications of HAR technologies combined with metaheuristic algorithms are profound. Improved patient monitoring and tailored rehabilitation protocols can lead to better health outcomes and lower healthcare costs. In sports, optimized training and injury prevention strategies can prolong athletes' careers while enhancing their performance. In terms of security, advanced surveillance capabilities can bolster public safety and protect critical infrastructure [7].

In our systematic review, we explored the technical complexities of employing metaheuristic algorithms in HAR by assessing their strengths and limitations in optimizing these systems. By analyzing recent advancements and considering future research directions, we aim to provide a comprehensive understanding of how metaheuristic algorithms can be applied within HAR. This exploration not only highlights the current state of the field but also serves as a foundation for future innovations that could unlock even more sophisticated HAR capabilities. As a response to curiosity towards the capability of metaheuristic algorithms in HAR, the following research questions (RQ) were developed as part of this work:

RQ1: How do metaheuristic algorithms enhance feature selection and improve the performance of machine learning models in human activity recognition compared to traditional feature selection methods?

RQ2: What are the most effective adaptations and enhancements for metaheuristic algorithms that have proven to be most effective for human activity recognition?

RQ3: What are the computational challenges faced by metaheuristic algorithms in human activity recognition?

RQ4: What are the emerging trends and significant research gaps in the application of metaheuristic algorithms for human activity recognition?

This research advances the field of metaheuristic algorithm in HAR with the following key contributions and implications:

1) Identify enhanced feature selection and optimization: This study demonstrates how metaheuristic algorithms improve feature selection and classification accuracy in HAR, reducing redundancy and computational costs while maintaining high recognition performance.

2) Insight into the advancement of hybrid metaheuristic approaches: By reviewing recent hybrid metaheuristic techniques, this research highlights their role in overcoming the limitations of individual algorithms, leading to more robust and efficient HAR systems.

3) Theoretical and practical insights: This study offers both theoretical contributions and practical considerations, helping researchers and practitioners navigate key challenges in optimizing HAR systems.

4) Bridging research and innovation: By analyzing emerging trends, this work serves as a foundation for future advancements, encouraging further exploration of novel strategies in HAR optimization.

The rest of this paper is organized as follows: Section II provides a review of related works. Section III presents the review method used for this research where it highlights the use of PRISMA approach. Section IV presents the results and discussions of this research to answer the research questions that have been raised. Finally, Section V presents the conclusion of the entire research work.

II. Related Work

The integration of metaheuristic algorithms into HAR systems has garnered significant scholarly attention, driven by the need to optimize feature selection, classification accuracy, and computational efficiency in complex sensor-driven environments. Prior studies have explored diverse applications of metaheuristics, though gaps persist in systematic evaluations of algorithmic adaptations and scalability challenges.

Helmi et al. [8] conducted a foundational analysis of nine metaheuristics, including Marine Predators Algorithm (MPA) for HAR and fall detection, demonstrating their efficacy in binary classification tasks. While their work established the viability of swarm intelligence for sensor data optimization, it focused narrowly on fall detection scenarios, leaving broader HAR applications underexplored. Similarly, Al-Wesabi et al. [9] employed Chaos Game Optimization to tune BiLSTM hyperparameters, achieving 93.9% accuracy on the UCI-HAD dataset, yet their methodology neglected feature selection dynamics critical for real-time deployment.

Recent advancements in hybrid metaheuristics have reshaped the field. Zhang et al. [10] introduced Oppositional and Chaos Particle Swarm Optimization (OCPSO), which elevated MI-1DCNN classification precision to 97.92%, outperforming conventional PSO-SVM models by 2.82%. Parallel developments by Tian et al. [11] utilized Improved Binary Glowworm Swarm Optimization to achieve 98.25% F-scores in ensemble learning frameworks, though their analysis omitted computational cost comparisons across algorithm classes.

Prior systematic analyses in metaheuristic research have emphasized breadth of algorithmic coverage over domain-specific methodological evaluation. Foundational works like Alorf's [7] meta-analysis provided comprehensive taxonomies of optimization techniques but offered limited assessment of their practical implementation efficacy in HAR contexts. Subsequent domain-focused reviews, such as Raj et al.'s [3] examination of healthcare applications, demonstrated rigorous vertical analysis while overlooking horizontal scalability across activity recognition domains. The field has seen notable technical innovations like Challa et al.'s [12] Rao-3 algorithm for BiLSTM optimization, which achieved benchmark performance across multiple datasets but left unexplored synergies with emerging deep learning architectures. This pattern reveals a persistent dichotomy in the literature between expansive algorithmic surveys and narrowly focused application studies, creating critical knowledge gaps in cross-domain performance evaluation and architectural hybridization potential, especially in the HAR domain.

III. Review Method

This review was conducted according to best practices in scoping reviews and is reported according to the PRISMA scoping review reporting guidelines [13].

A. Eligibility Criteria

This systematic review, conducted in Jan 2024, explored the application of metaheuristic algorithms in HAR, focusing on recent advancements from 2019 to 2024. The review included studies from the Scopus, IEEE Xplore, and Web of Science databases, specifically targeting journal articles and conference proceedings with keywords related to HAR, such as "recognition," "estimation," "classification," and "detection," as well as metaheuristic optimization algorithms through terms like "application" and "implementation." Non-essential materials, including book chapters, reviews, and articles in press, were excluded to maintain academic rigor. The timeline was restricted to the last five years to ensure the review reflected current knowledge, avoiding outdated methodologies. Only final, peer-reviewed publications were considered, and non-peer-reviewed sources, like book series and trade journals, were excluded. The review focused solely on English-language studies for consistency and convenience, ensuring it accurately represents the current landscape of metaheuristic algorithm applications in HAR. The inclusion and exclusion criteria are summarized in Table I.

TABLE I. THE INCLUSION AND EXCLUSION CRITERIA

Criteria	Inclusion	Exclusion
Timeline	2019-2024	>2024
Document type	Journal article, Conference paper	Other than mentioned in the inclusion criteria]
Publication stage	Final	Article in press
Exact keywords	Human activity recognition, activity detection, motion recognition, behaviour recognition, recognition, estimation, classification, detection, metaheuristic, optimization, application, implementation	[Other than mentioned in the inclusion criteria]
Source type	Journal, Conference proceeding	Book series, book, trade journal
Language	English	[Other than English]

B. Information Sources

Three major academic databases were used as information sources: Scopus, IEEE Xplore, and Web of Science. These databases focused on studies of metaheuristic algorithms and their applications in HAR.

C. Search

This study systematically reviews recent literature on metaheuristic algorithms for HAR. We conducted a comprehensive search using Scopus, IEEE Xplore, and Web of Science, focusing on peer-reviewed studies published between 2019 and 2024. The search strategy employed precise keywords related to metaheuristics and HAR to identify relevant studies.

Table II provides the detailed search strategies employed across three major academic databases: Scopus, IEEE Xplore, and Web of Science. The advanced query strings were carefully crafted to capture a comprehensive range of studies focusing on metaheuristic algorithms and their applications in HAR.

In Scopus, the search query included terms related to various metaheuristic algorithms like "evolutionary algorithm," "swarm intelligence," and "particle swarm optimization," combined with keywords associated with HAR, such as "recognition," "classification," and "detection.".

TABLE II. ADVANCED SEARCH QUERY

Database	Advanced search query string
Scopus	TITLE-ABS-KEY ((metaheuristic* OR "evolutionary algorithm*" OR "swarm intelligence" OR "genetic algorithm*" OR "particle swarm optimization") AND (algorithm* OR optimization* OR method*) AND (application* OR implementation* OR use) AND ("human activity recognition" OR har OR "activity detection" OR "motion recognition" OR "behavior recognition") AND (recognition* OR estimation* OR classification* OR detection*)) AND PUBYEAR > 2018 AND PUBYEAR < 2025 AND (LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp"))
IEEE Xplore	("Document Title":metaheuristic* OR "Document Title":"evolutionary algorithms" OR "Document Title":"swarm intelligence" OR "Document Title":"genetic algorithms" OR "Document Title":"particle swarm optimization") AND ("All Metadata":algorithm* OR "All Metadata":optimization* OR "All Metadata":method*) AND ("All Metadata":application* OR "All Metadata":implementation* OR "All Metadata":use) AND ("All Metadata":"human activity recognition" OR "All Metadata":"activity detection" OR "All Metadata":"motion recognition" OR "All Metadata":"behavior recognition") AND ("All Metadata":recognition* OR "All Metadata":classification* OR "All Metadata":detection*)
Web Of Science	TS=((metaheuristic* OR "evolutionary algorithm*" OR "swarm intelligence" OR "genetic algorithm*" OR "particle swarm optimization") AND (algorithm* OR optimization* OR method*) AND (application* OR implementation* OR use) AND ("human activity recognition" OR HAR OR "activity detection" OR "motion recognition" OR "behavior recognition") AND (recognition* OR estimation* OR classification* OR detection*)) and 2024 and 2023 or 2022 or 2021 or 2020 or 2019 (Publication Years) and Article (Document Types) and English (Languages)

In Scopus, the search query included terms related to various metaheuristic algorithms like "evolutionary algorithm," "swarm intelligence," and "particle swarm optimization," combined with keywords associated with HAR, such as "recognition," "classification," and "detection.".

The query string used for IEEE Xplore follows a similar format, specifying document types such as conference papers and journal articles while filtering by publication stage to exclude in-progress works. To ensure consistent and comparable results across all databases, the same keywords related to metaheuristics and HAR were applied throughout.

In Web of Science, the search strategy also included combinations of relevant keywords and was refined further by applying filters for document type, publication years, and language. By aligning the search terms and filters across these databases, this review aimed to ensure a consistent and thorough collection of relevant literature. These query strings play a crucial role in ensuring the systematic review captures the most relevant and high-quality studies within the specified timeframe, providing a robust foundation for the subsequent analysis.

D. Data Extraction Process

Fig. 1 shows a PRISMA diagram for the systematic process we undertook to identify and select the most relevant studies for our review on the application of metaheuristic algorithms in HAR. Our initial search across Scopus, IEEE Xplore, and Web of Science databases produced 159 articles.

To refine our dataset, we used Mendeley Reference Manager to eliminate duplicates, resulting in 122 unique articles. We then conducted an initial screening based on the titles and abstracts. During this phase, we excluded 78 articles for various reasons: some had unavailable full texts (3 articles), others focused primarily on vision-based approaches (8 articles), and a significant number did not closely align with the specific focus of our review (67 articles).

Following this, 44 articles underwent a rigorous full-text review. This in-depth assessment resulted in the exclusion of 17 articles primarily due to methodological shortcomings or insufficient relevance to our review's objectives. Ultimately, 27 studies met the inclusion criteria and were qualitatively synthesized to gain insights into the application of metaheuristic algorithms in HAR. These 27 selected papers were then meticulously examined and assessed to extract relevant information aligned with each research question, guided by the rationale outlined in Table III.

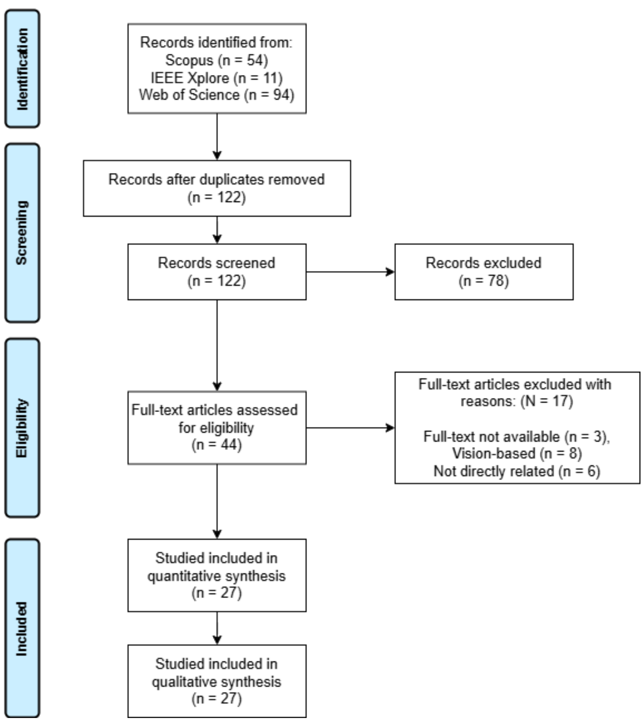


Fig. 1. PRISMA diagram.

TABLE III. RESEARCH QUESTIONS AND THEIR CORRESPONDING RATIONALES

Number	Research Questions	Rationale
RQ1	How do metaheuristic algorithms enhance feature selection and improve the performance of machine learning models in human activity recognition compared to traditional feature selection methods?	This question explores how advanced optimization techniques address persistent challenges in feature selection and model performance by reducing redundancy and improving predictive accuracy across various applications.
RQ2	What are the most effective adaptations and enhancements for metaheuristic algorithms that have proven to be most effective for human activity recognition?	This question investigates diverse adaptations and enhancements applied to metaheuristic algorithms, showcasing how these modifications enhance their effectiveness, adaptability, and efficiency for complex optimization problems.
RQ3	What are the computational challenges faced by metaheuristic algorithms in human activity recognition?	This question identifies significant computational challenges arising in the implementation of metaheuristic algorithms and offers insights into strategies for addressing these barriers effectively.
RQ4	What are the emerging trends and significant research gaps in the application of metaheuristic algorithms for human activity recognition?	This question uncovers transformative trends reshaping the field and highlights critical research gaps to provide a roadmap for future innovations and deepen understanding of these algorithms' potential.

IV. RESULTS AND DISCUSSIONS

In this section, we investigate all final selected articles (27 articles). The data is discussed to address the four mentioned research questions.

A. Improvement of Machine Learning Performance by Metaheuristic Algorithms over Traditional Methods Feature Selection (RQ1)

HAR rely heavily on the quality and relevance of the features extracted from sensor data. Traditional feature selection methods, while offering a certain level of effectiveness, can struggle with the complexities inherent in HAR tasks. Metaheuristic algorithms have emerged as powerful tools, offering significant advantages over traditional approaches. Fig. 2 shows the general workflow of how metaheuristic algorithm is being used to do feature selection. Feature selection happens after feature extraction, and metaheuristic algorithm will be applied during feature selection phase, though there are many approaches in applying metaheuristic algorithms during this phase.

One of the key strengths of metaheuristic algorithms is their ability to efficiently navigate large and complex search spaces. Unlike traditional feature selection methods, which may become stuck in local optima, metaheuristics employ a broader search strategy inspired by natural phenomena. Algorithms such as Genetic Algorithms (GA) and Grey Wolf Optimizers (GWO) mimic processes such as evolution and predator-prey interactions, respectively, to explore diverse regions within the feature space [14], [15]. This global search capability allows them to identify feature subsets that traditional methods might miss, potentially leading to superior classification performance in HAR applications.

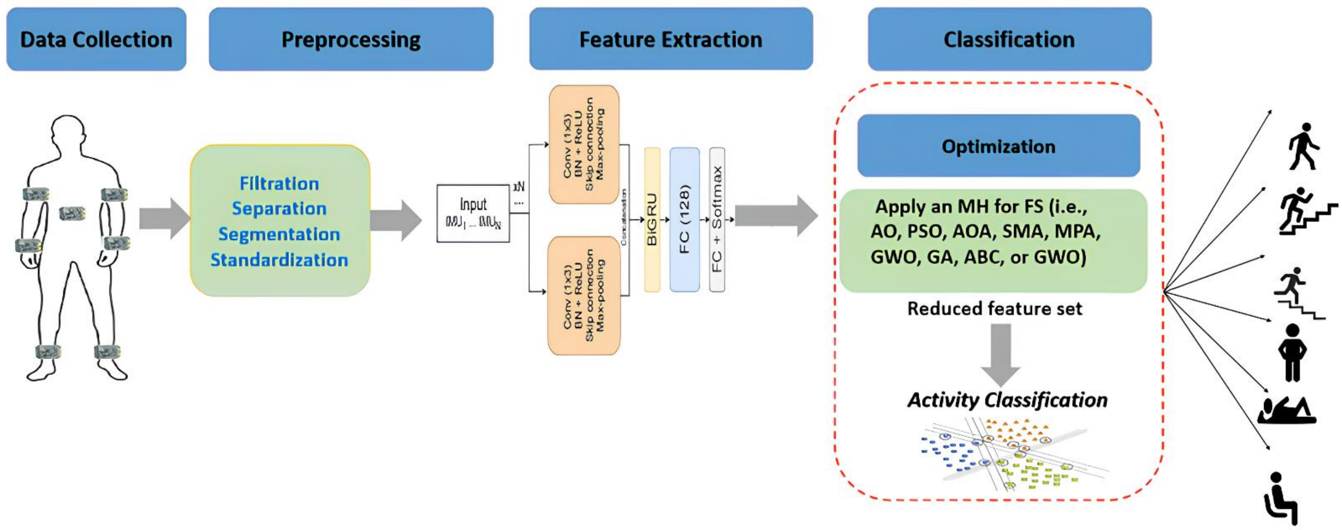


Fig. 2. Process workflow of metaheuristic feature selection for HAR [8].

Furthermore, metaheuristic algorithms play a key role in optimizing selected features by minimizing redundancy and identifying a small yet highly relevant set of features. This not only improves classification accuracy but also reduces the computational costs associated with managing large feature sets. These advantages make metaheuristic algorithms particularly valuable in critical medical applications, where both efficiency and accuracy are essential for reliable diagnoses. In contrast, traditional methods often rely on manual feature engineering or simpler optimization techniques, which may struggle to achieve the same level of efficiency or effectively capture the complex patterns found in sensor data used for HAR [16].

The fusion of heuristic algorithms and deep-learning approaches further boosts the benefits of feature selection in HAR. Deep-learning models demonstrate proficiency in unveiling intricate associations within data; however, they frequently require substantial quantities of high-quality features for optimal efficiency. By integrating metaheuristic algorithms into a deep learning framework, researchers can leverage their feature selection capabilities to pinpoint the most relevant features for a given task. This enhancement not only improves the training procedure but also results in models that exhibit greater resilience and generalizability [16]. For example, Alam et al. [17] has introduced NeuroHAR in 2024, which integrated Multilayer Perceptron (MLP) with Real-valued Genetic Algorithm (RGA). MLP performs the deep learning task of understanding and classifying complex human activity patterns, while RGA optimizes the hyperparameters by iterating through combinations to find the optimal model configuration. This synergy allows NeuroHAR to execute fewer models while exploring comprehensive hyperparameter ranges, making it computationally efficient while maintaining high prediction accuracy. Furthermore, the inherent adaptability of numerous metaheuristic algorithms enables them to manage the varied and high-dimensional characteristics of the sensor data commonly encountered in HAR applications. This adaptability makes them strong tools for researchers and developers to advance in HAR.

Metaheuristic algorithms have shown superior performance compared to traditional feature selection methods in effectively and adaptively handling high-dimensional data in HAR tasks. These approaches excel at navigating complex search spaces, enabling the discovery of optimal or near-optimal feature subsets that improve recognition performance. While earlier studies primarily relied on manual feature extraction and selection, the adoption of metaheuristic algorithms in HAR represents significant progress. By automating and refining this process, these algorithms address challenges related to feature interpretability and dimensionality, marking a substantial advancement in the field.

B. *Effective Adaptation and Enhancement of Metaheuristic Algorithms for HAR (RQ2)*

Researchers have investigated how metaheuristic algorithms can be tailored for systems related to HAR by analyzing a variety of approaches aimed at enhancing their effectiveness. The application of GAs has played a key role in the field of feature selection and classifier optimization, with significant achievements noted in Reweighted GAs, which have displayed remarkable accuracy in detecting daily activities. Furthermore, studies have shown their effectiveness in optimizing Support Vector Machines (SVMs) for HAR tasks [18], [19], [20], [21]. PSO has also displayed potential, especially in conjunction with SVMs (referred to as PSO-SVM), leading to enhancements in both detection accuracy and optimization efficiency [22]. Additional adaptations, including Quantum-behaved PSO (QPSO) and conventional PSO have shown advantages in refining kernel extreme learning machines (KELMs) and base extreme learning machines (ELMs), respectively, within the context of HAR [23].

Moreover, researchers have explored hybrid approaches that combine metaheuristic algorithms to address HAR challenges effectively. Hybrid techniques such as Hybrid Artificial Bee Colony and PSO (hABCPSO) and Oppositional and Chaos PSO (OCPSO) have demonstrated superior performance by leveraging the strengths of different algorithms to enhance feature selection, classifier parameter optimization, and overall recognition accuracy [24]. In addition to GAs and PSO, other metaheuristic algorithms, such as Chaos Game Optimization

(CGO), Binary Cuckoo Search (BCS), Rao-3 Optimization, Improved Binary Glowworm Swarm Optimization (IBGSO), and Gradient-based Grey Wolf Optimizer (GBOGWO), and Improved Cat Swarm Optimization (ICSO) have been adapted to fine-tune hyperparameters, explore search spaces efficiently, and improve the recognition performance of HAR [25], [26], [27].

Table V shows that metaheuristic algorithms have demonstrated superior and more efficient adaptation than conventional methodologies. Some enhanced metaheuristic algorithms even showed their superiority over the base-type metaheuristic algorithms. In contrast to traditional techniques that depend on manual feature engineering, metaheuristic algorithms automate the feature selection process, consequently enhancing the robustness and adaptability of HAR. Conversely, hybrid metaheuristic approaches, which combine the capabilities of algorithms such as GA and PSO, exhibit enhanced performance in terms of accuracy and computational efficiency when compared with conventional machine-learning models that typically require extensive data preprocessing and feature selection. Although traditional feature selection methods are simple and easy to understand, but metaheuristic algorithms provide a more powerful and flexible solution for complex HAR optimization, though they come with computational challenges.

C. *Computational Challenges and Influence on Metaheuristic Algorithms for HAR (RQ3)*

This research question discussed the key computational challenges encountered by metaheuristic algorithms in HAR and explored how these challenges influence their design and implementation. The computational challenges identified in the studied papers can be classified into two categories: Algorithmic Complexity, and Data Complexity as shown in Table IV.

TABLE IV. ALGORITHMIC AND DATA COMPLEXITY

Category	Computational Challenges
Algorithmic Complexity	Randomness, Premature Convergence, Complexity, Balancing Exploration and Exploitation, Slow Learning, High Computation Time
Data Complexity	Insufficient, Irrelevant, or Redundant Features, High Dimensionality, Computation Cost

Challenges related to algorithmic complexity include randomness, premature convergence, complexity, balancing exploration and exploitation, slow learning, and high computation time. Randomness is inherent in many metaheuristic algorithms and can lead to inconsistent results. Premature convergence occurs when the algorithm gets stuck in a local optimum and is unable to find the global optimum. Slow learning alludes to the prolonged duration required for the algorithm to effectively grasp and derive insights from the dataset, thus hindering the overall efficiency of the learning process. The high computational time stems from the fact that metaheuristic algorithms must evaluate a large number of possible solutions. On the other hand, challenges related to data complexity include insufficient, irrelevant, or redundant features, high dimensionality, and computation cost. High dimensionality points to the fact that the dataset comprises a wide range of features, thereby presenting a challenge for the algorithm to detect underlying patterns within the data. Moreover, the presence of insufficient, irrelevant, or redundant features within the dataset could also significantly hinder the efficiency of the algorithm, resulting in less-than-optimal outcomes. Table VI summarizes the computational challenges faced by the papers studied.

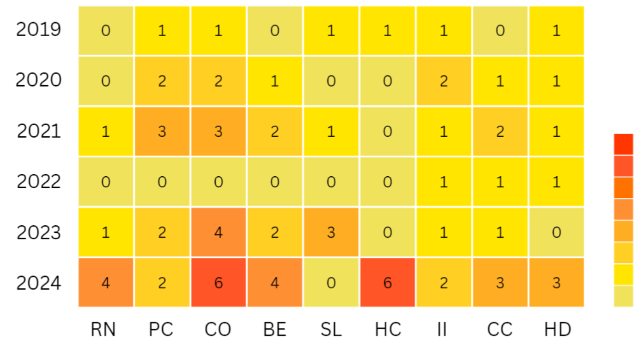


Fig. 3. Heatmap of computational challenges from 2019 to 2024.

From Fig. 3, it is proven that the computational challenges faced by metaheuristic algorithms in HAR have evolved over the years from 2019 to 2024. The most frequently encountered challenge appears to be balancing exploration and exploitation, particularly peaking in 2024 with four instances. This indicates a growing concern within the research community regarding the need for algorithms to effectively navigate the trade-off between exploration and exploitation of new solutions. This balance is crucial for optimizing algorithm performance without getting trapped in local optima or failing to converge on a global solution. The consistent presence of this challenge across the years underscores its significance in the field of HAR.

An increasing focus on complexity and high computation time has also emerged as a notable trend. This review has shown the complexity challenge grew steadily from 2019 to 2024, peaking in 2024 and maintaining a significant presence in subsequent years. Complexity was the most prominent challenge identified, accounting for 59.26% (16 out of 27) of the studies reviewed. This indicates that as metaheuristic algorithms grow more sophisticated, managing their complexity becomes increasingly critical. Similarly, high computation time saw a sudden spike in 2024, highlighting the significant computational burden of implementing advanced algorithms. This trend underscores the need for more efficient computational strategies or improved hardware to handle the intensive processing demands of metaheuristic algorithms in HAR applications.

Interestingly, some challenges such as randomness and premature convergence have relatively lower but varying instances across the years, with a noticeable spike in randomness in 2024. This variability might be due to the differing nature of the studies each year and the specific focus of the metaheuristic algorithms applied. The persistent challenge of insufficient, irrelevant, or redundant features shows that feature selection remains a critical area needing attention, impacting the accuracy and effectiveness of HAR.

TABLE V. METAHEURISTIC ALGORITHMS IN HUMAN ACTIVITY RECOGNITION

Metaheuristic Algorithm		**Effective adaptation**	**Classifier**	**Performance**
Base-type	**Enhanced-type**			
Particle Swarm Optimization (PSO)	Data not available (NA) [28], [29]	Optimal sensor combination through randomness and convergence.	SVM, RF, CNN, DNNLSTM, DeepCNN	SVM has the highest accuracy (95.13%)
	Oppositional and Chaos PSO (OCPSO) [10]	Helps in feature selection and improving recognition accuracy.	MI-1D-CNN	Results: • Precision: 97.92% • Recall: 97.85% • Accuracy: 97.81% • F1-score: 97.87%
	Quantum Behaved PSO (QPSO) [23], [30]	Enhances and optimizes kernel extreme learning machine (KELM) for HAR, resulting reduced misrecognized samples.	QPSO-KELM	QPSO-KELM shows highest accuracy at 91.3% for LDA and 96.2% for KDA [23] Accuracy of 96.4% [30]
	Hybrid Artificial Bee Colony and PSO (hABCPSO) [24]	Enhances local and global search capabilities for optimization.	Stacked AutoEncoder (SAE)	Has the most best performance values (17 out of 30 runs) over its competitors (ABC, DE, PSO, GA)
	PSO-Support Vector Machine (PSO-SVM) [22], [31]	PSO-SVM enhances detection accuracy, reliability, and optimization efficiency for SVM parameters.	PSO-SVM	Overall accuracy of 94.0% [22] Accuracy of 92.30%, F-Measure of 92.63% [31]
	Hierarchical PSO (H-PSO) [32]	Optimizes architecture-level parameters and layer-level hyperparameters simultaneously, enhancing the search for optimal configurations in CNNs.	1D-CNN	Accuracy on dataset: • UCI-HAR: 99.72% • PAMAP2: 96.03% • Daphnet Gait: 98.52% • Opportunity: 99.82%
	Adaptive Binary PSO (ABPSO) [33]	ABPSO utilizes a self-adaptive operator pool to enhance the feature selection process.	SVM & KNN	Accuracy: ReliefF: 95.62% (with 293 features selected) mRMR: 95.80% (with 201 features selected)
Biogeography Based Optimization (BBO)	Reweighted GA (rGA) [19]	Helps achieve high recognition accuracy of daily activities.	Reweighted Genetic Algorithm (rGA)	Accuracy on dataset): • CMU-MMAC: 88% • WISDM: 88.75% • IMSB: 83.33%
Bee Swarm Optimization (BSO)	BSO with deep Q-network (BAROQUE) [14]	BAROQUE lbalances exploitation and exploration for feature searching. It provides self-organization and self-adaptation capabilities for optimization.	KNN	Performance (accuracy on dataset): • UCI-HAR:98.41%
Cuckoo Search (CS)	NA [34]	Effectively contributed om high predictive accuracy due to its global convergence and efficient search space exploration.	NA	The accuracy value is 93.77% .
	CS with Recursive Feature Elimination (CSRFE) [21]	Optimizes the feature selection process, significantly reducing the number of features while maintaining or improving classification accuracy, minimizing temporal complexity in HAR systems.	SVM, RF, LR	Accuracy by classifier: RF: 96.76% SVM: 96.23% LR: 96.16%
Rao-3 Optimization	NA [12]	Optimization technique for ideal hyperparameters value to improve recognition performance.	BiLSTM	Accuracy on dataset: • PAMAP2: 94.91% • UCI-HAR: 97.11% • MHEALTH: 99.25%
Glowworm Swarm Optimization (GSO)	Improved Binary GSO (IBGSO) [11]	Enhances learning by selects a superior subset for ensemble pruning to find optimal subensemble models.	IBGSO	• Precision: 98.25% • Recall: 98.17% • Accuracy: 98.25% • F-score: 97.94%
Grey Wolf Optimizers (GWO)	Gradient-based Optimization & GWO (GBOGWO) [16]	Improves performance by balancing exploration and exploitation stages.	SVM	Mean accuracy: 98.87%
Chaos Game Optimization (CGO)	NA [9]	Fine-tunes BiLSTM hyperparameters for enhanced performance.	BiLSTM	UCI-HAR dataset: • Precision: 77% - 80.1% • Recall: 75.9% - 79.3% • Accuracy 92.0% - 93.2% • F-score: 76.0% - 79.4% UCI-HAD dataset:

				• Precision: 81.4% • Recall: 81.1% • Accuracy: 93.9% • F-score: 81.0%
Genetic Algorithm (GA)	NA [15], [18], [20], [26], [35], [36]	Used for selecting important features to improve classification performance while keeping the model small. It helps increase accuracy by filtering out noise and is also effective in optimizing fuzzy logic systems.	Deep Neural Decision Forest [18] KNN, SVM, RF [15] NA [20] SVM & RF [36] DCNN-LSTM [26] KNN [35]	[18] Accuracy: • ExtraSensory: 88.25% • Sussex-Huawei: 96.00% [15] F-measure: • KNN: 98.2% • SVM: 98.2% • RF: 97.6% [20] Accuracy: 99.1% [26] Result: • F1 Score: 98.89% • Average Recall: 99.01% • Average Precision: 98.90% • Total Accuracy: 99.92% [35] Accuracy using MHEALTH dataset is the highest.
	GA with a centroid-based clustering approach [36]	Helps in managing data efficiently while retaining high classification accuracy.	SVC, RF, KNN	Accuracy on dataset: • UCI-HAR: 93.45% • WISDM: 72.8%
	Non-dominated Sorting GA II (NSGA-II) [37]	Using a multi-objective optimization approach that simultaneously evolves LSTMs for classification accuracy.	LSTM	Classification accuracy on SMARTPHONE dataset: • With NGSA-II: 99.03% • Without NGSA-II: 97.69%
	Real-valued GA (RGA) with Multilayer Perceptron (MLP) [17]	Dynamic optimization of network architectures and hyperparameters, which allows for better handling of task complexities compared to traditional methods.	MLP	Accuracy based on model: NeuroHAR: 89.91% Grid Search:84.04% Notes: NeuroHAR is the proposed model (RGA with MLP).
Cat Swarm Optimization (CSO)	Improved CSO (ICSO) [27]	Improves CNN parameter tuning for HAR tasks.	CNN	ICSO-CNN achieved an accuracy of 99.79%, outperforming other methods such as CNN with Long Short-Term Memory (CNN-LSTM), PSO based CNN (PSO-CNN), and CNN-BiLSTM.

TABLE VI. COMPUTATIONAL CHALLENGES

ID	Paper	Computational Challenges								
		RN	PC	CO	BE	SL	HC	II	CC	HD
ID1	[28]	✓	✓							
ID2	[29]		✓	✓	✓					
ID3	[10]		✓			✓				
ID4	[30]		✓							
ID5	[23]					✓	✓	✓		
ID6	[24]								✓	
ID7	[22]		✓						✓	
ID8	[31]			✓						✓
ID9	[19]		✓	✓	✓					
ID10	[18]			✓	✓	✓				
ID11	[15]			✓	✓					
ID12	[20]			✓				✓		✓
ID13	[36]			✓						
ID14	[26]	✓								
ID15	[35]							✓	✓	
ID16	[14]			✓		✓				
ID17	[25]			✓						
ID18	[34]		✓					✓		
ID19	[12]			✓		✓				
ID20	[11]							✓	✓	✓
ID21	[16]		✓		✓			✓	✓	✓
ID22	[33]	✓		✓	✓		✓	✓	✓	✓
ID23	[21]	✓		✓	✓		✓	✓	✓	✓
ID24	[37]		✓	✓	✓		✓			
ID25	[27]	✓		✓			✓			✓
ID26	[17]			✓			✓		✓	
ID27	[32]	✓	✓	✓	✓		✓			

Abbreviations: RN = Randomness, PC = Premature Convergence, CO = Complexity, BE = Balancing Exploration and Exploitation, SL = Slow Learning, HC = High Computation Time, II = Insufficient, Irrelevant, or Redundant Features, CC = Computation Cost, HD = High Dimensionality.

In HAR, metaheuristic algorithms face various computational challenges that shape their design and implementation. Table VII summarizes these challenges across 27 reviewed papers, highlighting issues such as complexity and the need for balancing exploration and exploitation. Hybrid models that combine multiple algorithms are essential to address these challenges by leveraging their individual strengths. For example, combining GA with PSO achieves a balance between exploration and exploitation, while hybrid approaches like ABC with PSO tackle complexity and premature convergence by using ABC for local search and PSO for global optimization.

High-dimensional data and redundant or irrelevant features significantly affect classification accuracy, with 55.56% (15 out of 27) of studies identifying this as a critical challenge. To address this, efficient feature selection techniques, such as using QPSO to optimize feature sets, have improved KELMs by retaining only the most discriminative features. Additionally, computational overhead, including high processing times and costs, poses scalability challenges for HAR systems. One solution has been implementing BBO within scalable architectures, dynamically optimizing resource allocation to manage system load and reduce computational demands.

The efficiency of feature selection and extraction is another critical area influenced by high dimensionality and slow learning processes, impacting 59.26% (16 out of 27) of the studies. IBGSO, for instance, enhances the learning process by identifying high-value features and reducing redundancy, thereby increasing overall system efficiency. As HAR systems increasingly demand real-time processing capabilities, algorithmic designs must focus on minimizing computational burdens without compromising accuracy, ensuring these systems are both effective and scalable for practical applications.

Additionally, intensive numerical calculations demand high computational resources; despite not being much, 4 out of the 27 papers studied have impacted the feasibility and scalability of designs. The iterative nature of the optimization process necessitates frequent updates and fitness value calculations, contributing to computational intensity. Addressing optimal training to prevent underfitting or overfitting entails computational hurdles, prompting the design of early stopping mechanisms. The transition from handcrafted feature extraction to deep learning techniques, driven by the limitations of traditional machine learning, introduces further computational demands [35]. The real-time processing requirements inherent in HAR pose significant computational challenges, guiding the selection of sensors and algorithms. Also, from Fig. 3 we can see that from 2019 to 2024, most of the challenges faced were algorithmic complexity compared to data complexity. In six years since 2019, the cumulative computational challenges faced by the papers studied were 76, and algorithmic complexity contributed 53 (69.74%) from the total, while data complexity contributed 23 (30.26%) in total, though both categories showed an increasing pattern over the years and peaked in 2024.

Metaheuristic algorithms offer a flexible strategy for optimizing intricate issues in HAR, unlike conventional techniques that might necessitate explicit mathematical formulations. Traditional machine learning approaches typically rely on predefined models and assumptions, limiting their ability to adapt to the dynamic nature of human activities. In contrast, metaheuristic algorithms seek solutions based on heuristic principles, enabling more resilient HAR solutions. The development of metaheuristic algorithms is guided by the need to balance exploration and exploitation to efficiently navigate the search space of HAR problems, a challenge less prominent in traditional optimization methods. Computational obstacles such as dimensionality and local optima are more effectively tackled by metaheuristics through population-based search strategies, a capability that traditional methods may struggle to achieve.

TABLE VII. INFLUENCE OF COMPUTATIONAL CHALLENGES TO DESIGN

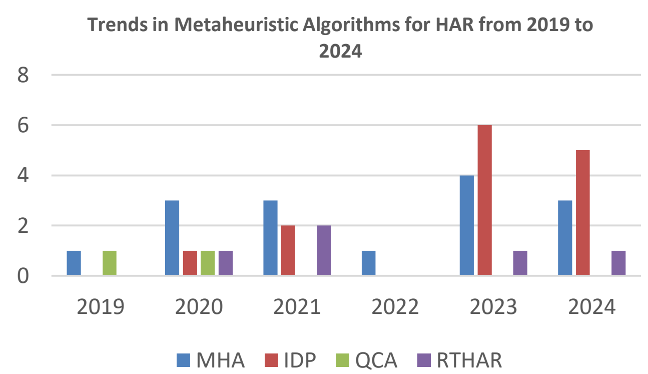
ID	Paper	Influence on Design			
		Hybrid model	**Low Classification Accuracy**	**System scalability**	**Feature selection and extraction efficiency**
ID1	[28]				✓
ID2	[29]		✓		
ID3	[10]	✓	✓		✓
ID4	[30]	✓	✓		
ID5	[23]	✓	✓		✓
ID6	[24]	✓		✓	
ID7	[22]	✓	✓		
ID8	[31]	✓			✓
ID9	[19]	✓			✓
ID10	[18]		✓	✓	
ID11	[15]		✓		✓
ID12	[20]				✓
ID13	[36]		✓		
ID14	[26]		✓		✓
ID15	[35]		✓		✓
ID16	[14]				✓
ID17	[25]		✓		✓
ID18	[34]	✓			
ID19	[12]				✓
ID20	[11]	✓	✓		✓
ID21	[16]	✓	✓		✓
ID22	[33]	✓	✓	✓	✓
ID23	[21]	✓			✓
ID24	[37]	✓			
ID25	[27]	✓			
ID26	[17]	✓	✓	✓	
ID27	[32]	✓			

D. *Trends and Research Gaps of Metaheuristic Algorithm for HAR (RQ4)*

This research question explores the trends and research gaps in the use of metaheuristic algorithms for HAR between 2019 and 2024. A summary of the findings is provided in Table VIII. One notable trend is the rise of hybrid metaheuristic algorithms. These hybrid approaches, such as combining GAs with PSO, capitalize on the strengths of multiple algorithms to strike a balance between exploration and exploitation, tackle complexity, and improve convergence rates. For instance, hybrid models that integrate ABC and PSO algorithms have demonstrated potential in enhancing both local and global search capabilities. Another emerging trend is the integration of deep learning techniques with metaheuristic algorithms. Deep learning models, particularly CNNs and Recurrent Neural Networks (RNNs), are being employed to automate feature extraction and boost classification accuracy. In addition, the application of quantum computing in this domain is gaining traction, with QPSO showing promise for optimizing processes in high-dimensional spaces. The growing demand for real-time processing in HAR has also boosted the development of more efficient and scalable algorithms. For instance, techniques like BBO are being applied to dynamically optimize resource allocation, ensuring smooth and effective operations in real-time environments.

TABLE VIII. SUMMARY OF EMERGING TRENDS IN METAHEURISTIC ALGORITHMS FOR HAR

Trend	Description	Examples
Hybrid Metaheuristic Algorithms	Combining different algorithms to balance exploration and exploitation and improve convergence rates.	GA + PSO, ABC + PSO
Integration with Deep Learning	Using deep learning models to automate feature extraction and improve classification accuracy.	CNNs, RNNs combined with metaheuristics
Quantum Computing Applications	Enhancing optimization processes in high-dimensional spaces.	QPSO
Real-Time Processing in HAR Systems	Developing scalable algorithms for dynamic optimization in real-time environments.	BBO for resource allocation



Abbreviations: MHA = Hybrid Metaheuristic Algorithms, IDP = Integration with Deep Learning, QCP = Quantum Computing Applications, RTHAR = Real-Time Processing in HAR Systems

Fig. 4. Trends in Metaheuristic algorithms for HAR from 2019 to 2024.

Fig. 4 shows key trends in metaheuristic algorithms for HAR from 2019 to 2024, focusing on four major areas: Hybrid Metaheuristic Algorithms (MHA), Integration with Deep Learning (IDP), Quantum Computing Applications (QCA), and Real-Time Processing (RTHAR). Research on MHA has remained steady, peaking with four publications in 2023 before slightly dropping to three in 2024. This reflects the continued importance of hybrid approaches in tackling complex HAR challenges. IDP has emerged as the dominant focus, with publications surging to six in 2023 and maintaining strong momentum with five in 2024. This trend highlights the growing synergy between deep learning and HAR systems, showcasing its potential to enhance automation and accuracy. QCA, while still in the experimental stage, has seen consistent yet minimal activity, with one publication annually through 2020. This indicates ongoing exploration of quantum computing's potential in HAR. RTHAR, which focuses on real-time processing techniques, saw moderate activity with a peak in 2021 before stabilizing at one publication per year through 2024. This trend suggests a gradual shift toward standardization in real-time solutions for HAR. The sustained high levels of research in MHA and IDP through 2024 demonstrate the community's strong focus on advancing hybrid models and integrating deep learning, while interest in experimental and specialized methods like QCA and RTHAR continues to provide avenues for innovation.

Significant research gaps persist in HAR, as shown in Table IX despite the trends. A key challenge lies in the scalability and efficiency of metaheuristic algorithms when handling large datasets typical in HAR applications [30]. Many of these algorithms become computationally expensive with increasing data sizes, limiting their applicability in big data scenarios. Additionally, there is a lack of comprehensive studies comparing the effectiveness of various metaheuristic algorithms across HAR contexts. While individual algorithms have been explored, systematic comparisons across scenarios, such as sensor-based activity recognition in smart homes versus smartphone-based recognition during exercise, are needed to identify the most suitable options for specific applications. Combining deep learning with metaheuristic algorithms for hyperparameter optimization has improved HAR systems but understanding how these models interpret selected features remains a major gap. This lack of insight hampers our ability to evaluate the importance of features in accurately recognizing activities. Most studies focus on improving efficiency and accuracy, often overlooking computational costs and real-time feasibility, particularly in wearable sensor-based HAR systems. Addressing these challenges is crucial for developing practical, effective solutions that enhance seamless human activity recognition.

TABLE IX. SUMMARY OF RESEARCH GAPS IN METAHEURISTIC ALGORITHMS FOR HAR

Research Gap	Description
Scalability and Efficiency	Metaheuristic algorithms often struggle with computational costs as data sizes increase in HAR applications.
Lack of Comprehensive Comparisons	Insufficient studies comparing different metaheuristic algorithms across various HAR contexts.
Interpretability of Metaheuristic-Optimized Models	Limited research on understanding the significance of features selected by metaheuristic algorithms in HAR.
Real-Time Feasibility	Need for lightweight algorithms that can operate efficiently in real-time, especially in wearable sensor-based HAR.
Adaptability to Dynamic Environments	Lack of dynamic adaptive algorithms that can adjust to changing human activity patterns.
Integration with IoT and Edge Computing	Underexplored integration of metaheuristics with IoT devices and edge computing for practical HAR applications.

V. Conclusion

This systematic review underscores the transformative role of metaheuristic algorithms in advancing HAR, synthesizing insights across four research questions. The analysis revealed that metaheuristic algorithms such as GWO significantly enhance feature selection and classification accuracy (RQ1), achieving up to 96.00% recognition rates by efficiently navigating high-dimensional data and reducing redundancy. Hybrid and enhanced adaptations like OCPSO and Quantum-inspired PSO emerged as pivotal solutions (RQ2), boosting detection accuracy by 2.82% and optimizing models such as QPSO-KELM to 96.2% precision. However, computational challenges persist (RQ3), in which 69.74% are algorithmic complexity, and 30.26% are data complexity. Emerging trends (RQ4) highlight a shift toward hybrid metaheuristic algorithms, integration with deep learning, and quantum-inspired techniques which had peaked in 2024, yet gaps in scalability, real-time feasibility, and interpretability demand urgent attention. Collectively, metaheuristic algorithms demonstrate immense potential to revolutionize HAR not limited to healthcare, sports, and security, but future innovations must prioritize lightweight, adaptive frameworks to bridge practical implementation gaps and unlock their full societal impact.

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