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Bridging the Intelligence–Efficiency Gap: A Critical Review of Obstacle Avoidance in Human-Interactive Robots

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***Abstract* – Obstacle avoidance is considered a critical capability of Human Interaction Robot operating in dynamic shared environments with humans. Traditional and deep learning-based methods from 2019-2025 have been systematically reviewed in this paper to evaluate their applicability, performance, and real-world deployability in HIRs. Traditional approaches such as Bug algorithms, Vector Field Histogram (VFH+), and Dynamic Window Approach (DWA) provide real-time operation and low computational demands but lack adaptability to complex, human-centric scenarios. In contrast, deep learning techniques, including CNNs, LSTMs, and Deep Reinforcement Learning (DRL) deliver superior perception and adaptability yet impose high computational requirements that hinder edge deployment. Comparative analysis reveals that only about 18% meet the criteria of edge friendliness, while more than 59% require GPU support. However, gaps persist regarding sim-to-real transfer (over 70% sim testing only), benchmarks like BDD100K, and social compliance metrics' under-measurement. The contribution is threefold: (1) the integration of HRI challenges with the capabilities and limitations of DL; (2) the taxonomy and comparison of the state of the art, emphasizing the intelligence-efficiency gap in terms of accuracy, latency, and edge feasibility; and (3) the roadmap of HRI research, proposing the benefits of hybrid modular architectures, hardware-aware design, and explainability of AI systems. Ultimately, the future of HIR navigation will be driven by a hybrid approach that combines lightweight AI vision systems and strong rule-based control architectures.**

Keywords—Obstacle Avoidance, Human-Interactive Robots, Deep Learning, Intelligence–Efficiency Gap, Edge Deployment, Hybrid Architectures

I. INTRODUCTION

The Global service robot market size is projected to be worth $90 billion by 2030 (IFR, 2023) [1] as robots find greater applications in hospitals [2], households [3], and public spaces. Human Interaction Robots (HIRs) [4] are a revolutionary innovation, not only for tasks but also for interacting, assisting, and coexisting with human beings in common environments. Unlike industrial robots, which operate in structured environments, HIRs must move through cluttered, dynamic, and disordered indoor areas, often while coping with challenging social signals and safety boundaries. One of the most basic requirements of such robots is obstacle avoidance (OA), which is the capability to perceive obstacles and plan safe and efficient paths around them in real time. In such settings, obstacle avoidance [5] is a matter of safety, efficiency, and user satisfaction beyond the realm of navigation necessity. The technology has undergone significant improvements in recent years, impacting autonomous systems, robots, and assistive

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technologies. However, safe navigation of humans within the environment remains an urgent issue since unexpected pedestrians, moving obstacles, and social conventions necessitate real-time, adaptive obstacle avoidance (OA) systems. Traditional obstacle avoidance approaches using sensor-based modeling [6], handcrafted feature extraction [7] suffer from a lack of generalization to diverse environments and perform poorly in low-light conditions, complex indoor geometries, and areas with dense traffic. Robot perception and navigation have been transformed by deep learning, enabling robust feature extraction and decision-making capabilities. While deep learning (DL) has revolutionized OA in controlled settings, its integration with human-interaction robots (HIR) is vastly under-explored, and there exists a performance-usability gap. Deep learning (DL) has proven to be a good method for accomplishing strong and intelligent obstacle avoidance.

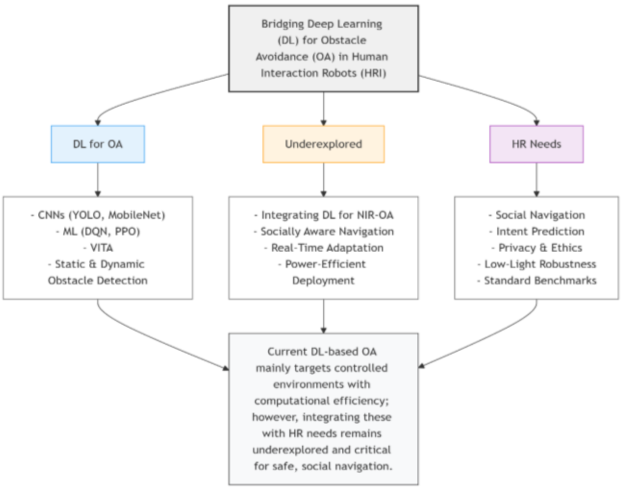

FIGURE 1. Conceptual diagram illustrating the research gap between current deep learning-based obstacle avoidance and the specific needs of Human Interaction Robots (HIRs)

Convolutional Neural Networks (CNNs) [8] have been highly successful in object detection and scene understanding, and attention-based models [9] such as Transformers, have also been promising in modeling global spatial dependencies for more accurate obstacle perception. Reinforcement Learning (RL) [10] methods also enable robots to learn adaptive navigation policies through trial and error. With its capability of learning high-level temporal and spatial features from raw sensory data directly, DL has surpassed traditional rule-based or heuristic methods in perception precision, flexibility, and decision-making. But integrating deep learning into human-interaction robots raises numerous challenges, like

- Unpredictable obstacle behavior (e.g., unexpected human movement).
- Social navigation requirements (e.g., personal space, eye contact).
- Hardware limitations (e.g., edge-device latency below 100ms).

This has led to growing interest in using Deep Learning (DL) as a subset of artificial intelligence capable of learning from raw sensor data and generalizing to new situations. DL enables robots to perceive the world using cameras, LiDARs, and other sensors and make intelligent, real-time decisions without being completely hard-coded. Current DL-based obstacle avoidance is used predominantly in controlled environments with good computational efficiency. But integrating these techniques with those for socially aware navigation on human interaction robots remains an untapped but significant topic for safe, adaptive systems. In light of the growing complexity and deployment challenges in robotic perception, the present study aims to answer the following research questions:

1. What are the state-of-the-art deep learning models used for human-interactive robot obstacle avoidance?
2. How does this model compare in terms of accuracy, inference latency, and deployment feasibility?
3. Where are the research gaps, and how can future work make DL-based OA systems more robust and deployable?

This paper covers algorithmic advances and emphasizes real-world deployment considerations such as speed–accuracy trade-offs, power budgets, hardware compatibility, and model size. The key contributions of this article are as follows:

1. **HIR-Centric Synthesis of Obstacle Avoidance:** The work presents a specific synthesis of traditional and deep learning-based methods of obstacle avoidance, specifically following the context of human-interactive robots, considering safety, social compliance, and deployment in real-world indoor scenarios.
2. **Deployment-Oriented Taxonomy and Comparative Evaluation:** This paper provides a structured taxonomy and unification comparison for analyzing methods based on "perception accuracy," "real-time latency," "model complexity," and "edge device feasibility," which are often neglected in the existing surveys.
3. **Identification of Practical Gaps and Actionable Research Directions**: Critical limitations in current methods, including sim-to-real, the absence of standardized evaluation metrics for HIR, and hardware limitations, are clearly presented, followed by suggestions of how to achieve efficiency, explanations, and human considerations in HIR in the near future.

The following part of this paper is organized: Section 2, Traditional Obstacle Avoidance Methods; Section 3, Deep Learning Methods; Section 5, Comparative Analysis and Critical Evaluation; Section 6, Open Challenges and Future Directions; Section 7, Conclusion and Future Work.

II. Traditional Obstacle Avoidance Methods: Establishing the Baseline

Traditional obstacle avoidance algorithms have been the backbone for mobile robot navigation over the last couple of decades. These rule-based or sensor-driven methods are still widely applied because they are simple, predictable, and low in computational cost, thus enabled in real-time on an edge device. They generally find themselves at a loss when confronted with dynamic, human-centric environments where unforeseen movements, social norms, and indoor layouts are so complex key challenges for human-interactive robots. Figure 3 is used to show the overall distribution of the algorithms implemented in the 16 HIR Obstacle Avoidance research studies (2019-2025).

Traditional approaches can be categorized into three main classes: reactive, deliberative, and hybrid.

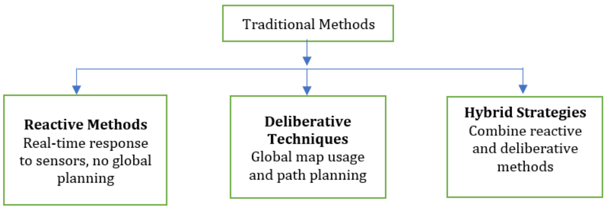

FIGURE 2. Classifications of traditional methods

A. Reactive Methods

Reactive Methods [11] Human-robot interaction (HRI) involves robots reacting instantaneously to human actions or environmental inputs online and not relying heavily on predetermined actions or expectations. This approach emphasizes responsiveness and flexibility, enabling robots to coexist harmoniously with humans in dynamic and uncertain environments. Key example and improvements include:

Adaptive VFH+ (AVFH+) [12]: Redefines obstacle density, incorporates dynamic thresholding, adaptive speed, and Bézier smoothing. This gives 35% smoother trajectories and a 20% decrease in time for dense environments, helpful for wheelchair navigation in human spaces.

Modified Pure Pursuit + VFH + LiDAR-SLAM [13]: This is a combination of adaptive path tracking and avoidance. The result is 40% less deviation during dynamic simulation, making it suitable for logistics and emergency vehicles.

Bug algorithm adaptations [14], [15]: Utilization of inexpensive proximity sensors along with dynamic corrections like angular thresholds or 50° wrist yaw that reduces 86% collision (from 11–12 to 2 collisions), pick-up success in human-cobot cells, but with limitations due to blind spots or kinematic limitations.

Free-configuration Eigenspace (FCE) [16]: Eigenvector analysis of the LiDAR scans which is better than VFH for handling static and dynamic obstacles, even in RoboCup competition scenarios, and computationally light

These models are extremely fast, edge-friendly, low cost with some shortcomings like poor generalization for unpredictable human motions, absence of social compliance, and frequent oscillations or dead zones.

B. Deliberative Technique

Deliberative architecture [17] is a fundamental concept in robotics where robots can make decisions and perform intricate tasks. Deliberative architecture refers to the capability of a robot to perceive its environment, reason about the state in question, and create a plan for a chain of activities to achieve its goals. It also uses global maps and planned paths. They are accurate in static environments, but slow and inflexible in dynamic ones. While deliberative algorithms afford the best route planning strategies, with clear trade-offs, the modified Dijkstra methods in [18], [19] excel in terms of compatibility with edge devices, such as the RK3588/STM32F1 series, and their ability to permit conflict-free control of multiple robots, even with limited enhancements in the route lengths, on the order of 1-3%. By comparison, the optimized version of the A* search algorithm that combines it with the Dynamic Window Approach (DWA) [20], [21] yields increased performance through reductions in the path lengths by up to 15-17% and turns by up to 58-75%, along with the ability to handle complex scenarios such as the "U-shaped trap;" however, the increased computation burden is not specified for resource-constrained platforms. Moreover, the optimized version targeting raw digital terrain [22] enables fast calculations but remains limited to platforms that have accessible geospatial maps. Most importantly, all these deliberative routes share the same failing characteristic as the HIR context, optimality in the context of static scenarios, suffering in highly dynamic ones due to high latency in replanning and the inability to account for unpredictable movements due to their static nature.

C. Hybrid Strategies

Hybrid methods combine reactive and deliberative approaches to balance speed and accuracy. They are more robust in semi-dynamic environments. Recent works have greatly improved hybrid obstacle avoidance, mainly by optimized variants of the Dynamic Window Approach. Advanced variants, including the ones with velocity-adaptive safety margins and threat classification [23] [24], have shown marked improvements and attained 37.3% faster avoidance, 16.8% shorter paths, 47.9% smoother trajectories, while maintaining real-time performance at 500 Hz suitable for edge devices. Further innovation has resulted in a human-imitation hybrid model that unifies DWA with deep learning of collision detection with 88.7% accuracy and human-like evasive maneuvers with 82.2% accuracy. This resulted in much better crowd navigation, with only 6 collisions out of 300 trials in simulated public spaces [25]. Other methods include the Finite Distribution Estimation-Based Dynamic Window Approach (FDEDWA), which enjoys robust performance at 153 FPS with instantaneous reaction to sudden obstacles [26], and FIDWA, utilizing fuzzy logic for dynamic adjustment of weights in planning and thereby reducing failure rates by 60% in diverse environments [27].

TABLE 1. Strengths and weaknesses of traditional (reactive, deliberative, and hybrid) obstacle avoidance methods

Ref	Type	Model	Strength	Weakness
Fang et al. [12]	Reactive	Vfh+ (avfh+) algorithm	Accurately perceive and avoid obstacles	Environmental dependency
Mondal et al. [13]	Reactive	Modified pure pursuit (MPP), vector field histogram (VFH), and lidar-based (SLAM)	Safe navigation even in complex situations	Heavily relies on lidar for both SLAM and VHF
Cichosz et al.[14]	Reactive	Bug algorithm	Collisions dropped from 11 to 2, and in orientation experiments	He wrist yaw angle's upper limit was bounded at 50° due to the kinematics and work cell layout, which might restrict its flexibility in certain scenarios
Zaheer et al. [16]	Reactive	Free-configuration eigenspace (FCE), a geometric and eigenvector-based approach	FCE effectively detects unknown obstacles and avoids collisions	Localization errors could potentially affect the accuracy of the FCE method.
Li et al. [15]	Reactive	Bug algorithm with proximity sensors	Lightweight algorithm with 86% collision reduction enables real-time safety on edge devices.	Limited 50° yaw angle and sensor blind spots cause occasional dead zones.
Celik et al. [18]	Deliberative	Dijkstra algorithm	Modified Dijkstra yields 1-3% shorter paths than the classical version.	Minor real-world path deviations from PID/motor tolerances.
Qu et al. [20]	Deliberative	A* algorithm and DWA algorithm	Achieves 15% shorter, smoother paths with reliable dynamic obstacle avoidance.	Increased computation time during dynamic avoidance; local optima in complex environments.
Labonte et al. [22]	Deliberative	A* graph optimization algorithm	Lightning-fast processing on raw images enables real-time navigation.	Sharp turns at obstacles limit practical vehicle use.
Zhou et al. [19]	Deliberative	Dijkstra algorithm	Enables conflict-free multi-robot coordination through dynamic path adjustment.	Increases travel distance/time for lower-priority robots during conflicts.
Han et al. [21]	Deliberative	Improved a* algorithm with the dynamic window approach	Faster path planning with dynamic adaptability.	Untested for large-scale robot fleets.
Cao et al. [23]	Hybrid	Improved dynamic window approach (DWA) algorithm	Faster obstacle avoidance (37.3%-time reduction) with safer navigation.	Struggles in complex, unmapped multi-robot environments.
Hahn et al. [24]	Hybrid	Dynamic window approach (DWA)	Superior dynamic obstacle avoidance	Struggles in complex multi-robot scenarios
Matsuzaki et al. [25]	Hybrid	Dynamic window approach (DWA)	Human-like efficient crowd navigation.	High computational demands are unquantified.
Lee et al. [26]	Hybrid	Finite distribution estimation-based dynamic window approach (FDEDWA)	Fast dynamic obstacle avoidance	Requires preprocessing steps
Abubakr et al. [27]	Hybrid	Adaptive dynamic window approach (DWA)	Adaptive weights improve dynamic obstacle avoidance.	Limited testing in high-speed scenarios.

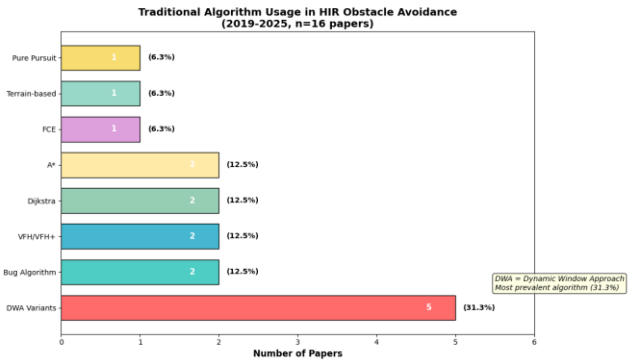

FIGURE 3. Distribution of traditional obstacle avoidance algorithms in hir research (2019–2025)

D. *Performance Analysis of Classical Obstacle Avoidance Algorithms*

Though traditional obstacle avoidance methods have established the foundation for autonomous robotic navigation, they vary significantly in computational complexity, dynamic obstacle handling, and applicability of deployment. In Table 1, the most dominant classical methods are contrasted to determine their suitability in modern human-interactive robotics.

The comparative survey of Table 1 indicates that reactive methods (e.g., Bug, VFH+) are simple and suitable for edge deployment but break down in complex or dynamic environments. Deliberative methods (e.g., A, Dijkstra) guarantee optimal path planning in static environments but are computationally expensive and unsuitable for real-time updating. Hybrid methods (e.g., DWA, FD-DWA) find a good trade-off, with improved flexibility in dynamic environments, though preprocessing is usually required, and large-scale or high-speed applications become troublesome.

III. Deep Learning Models for Obstacle Avoidance (Addressing RQ1)

Deep learning-based obstacle avoidance balances speed (YOLO, SSD), accuracy (feature extraction networks), and efficiency (local CNNs for indoor robots) against one another. Severe challenges include dealing with occlusions, edge deployment, and responsiveness in novel environments.

A. Optimized, Real-Time CNN Models

DRL-based approach by Joohyun et al. [28] applied the SMDP algorithm with the grid map for enhancing USVs' perception ability and ensuring COLREGs compliance. However, this approach increases the computation power requirement for USVs. Another DRL-based approach by Pengzhan et al. [29] used the Soft Actor-Critic with Prioritized Experience Replay for assisting USVs with the real-time path planning of the manipulator. In this approach, the large action space, as mentioned earlier, increases the computation power requirement. Another DRL-based approach by Xing et al. [30] proposed the ANOA based on the Dueling DQN. A Two-Stage Noisy Double DQN approach with CNN-based depth perception [31] achieved faster convergence but incurred substantial computational overhead. Contrastingly, the feasibility of edge deployment using IC-Net with network slimming has been shown by Yang et al. [32], resulting in 97.4% model size reduction without compromising accuracy and deployment feasibility. Michael et al. [33] utilized spatial encoding with LSTMs for pedestrian-adequate navigation, consequently improving responsiveness to multiple objects at the expense of increased computation, whereas Abhik et al. [34] improved maneuverability with DRL and recurrent networks with temporal attention, resulting in high memory usage. Rosli et al. [35] have shown the feasibility of cost-effective real-time obstacle avoidance using SSD MobileNetV2 with Jetson Nano, independent of expensive sensors, whereas Xi et al. [36] identified the need to address embedded deployment issues even with optimized CNNs, and Kento et al. [37] provided an overview of newly developed robotic frameworks with LLM and VLM, indicating increased usage in perception, planning, and control for obstacle avoidance

B. Transformer-Based Model

Transformer-based models, specifically Dual-Channel Self-Attention transformers by Changjian Lin et al. [38] improved feature extraction for UUV navigation by leveraging self-attention mechanisms to detect obstacles in low-visibility environments through multi-sensor data fusion. Despite achieving high accuracy (92.8%) and real-time performance (38 FPS), these models face deployment challenges on embedded systems due to their high computational complexity and power consumption. Table 2 shows the models' analysis based on performance below.

C. Hybrid CNN + LSTM/RNN Approaches

Alitappeh et al. [39] combined CNNs for spatial feature extraction and LSTMs for temporal sequence learning, achieving 96.1% accuracy and 42 FPS for real-time robotic navigation, though sequential processing in LSTMs may slow inference times. Saleem et al. [40] integrated CNN-based perception with decision-making using orientation, depth images, and IMU data, achieving 84.6% accuracy for precise real-time obstacle avoidance while balancing feature extraction and temporal processing.

D. Deep Reinforcement Learning (DRL) Approaches

Jianchuan et al. [41] Propose a DRL-based autonomous navigation method using pseudo-laser observations from a monocular camera, achieving a 90.2% success rate but facing challenges like high training time, computational cost, and hardware reliance. Xiaojun et al. [42]. and Lingping et al. [43] use self-supervised reinforcement learning for robot collision avoidance, tested on a UR3 robot with advanced safety-aware planning and pseudo-laser data, but require large training data and are sample-based. Patrick et al. [44] developed an end-to-end DRL-based obstacle avoidance system using monocular vision, but it struggles with sim-to-real transfer, requires extensive training data, and needs further adjustments for real-world deployment.

E. Comparative Table of Deep Learning Methods

Table 2 provides a comparative analysis of deep learning-based obstacle avoidance methods, contrasting their accuracy, real-time performance (FPS), embedded systems suitability, and computational cost. The values are aggregated based on reported figures in [28] – [44]; where specific numbers could not be determined, conservative estimates were calculated based on reported FPS, model size, or compute specifications.

TABLE 2. Structured comparison of deep learning approaches for obstacle avoidance

Criteria	**CNNs (YOLO, MobileNet, ICNet)**	**Transformers**	**Deep Reinforcement Learning**
Accuracy	84.6–97.4% (size reduction) [32], [40]	92.8% [38]	85–90% (success rate) [41] - [44]
Latency	30 – 70ms	40 – 120 ms	Highly variable (often >100ms) 50-200+ ms

Criteria	CNNs (YOLO, MobileNet, ICNet)	Transformers	Deep Reinforcement Learning
Training Data	Moderate (supervised)	Large (self-attention)	Very Large (trial-error)
Inference Speed	✅ Fast (optimized)	⚠️ Moderate	❌ Slow (sequential)
Edge Deployment	✅ Yes (lightweight variants)	❌ No (GPU required)	❌ No (high memory)
Adaptability	Static (retrain needed)	High (attention-based)	Very High (online learning)
Sim-to-Real Gap	Low	Medium	Very High
Primary Trade-off	Speed vs. contextual reasoning	Accuracy vs. power/latency bottlenecks	Adaptability vs. training cost & interpretability
HIR Safety	Medium (reactive, limited intent prediction)	Very High (multi-sensor fusion, complex scene understanding)	Medium-High (learns policies, poor sim-to-real safety guarantees)
Best for HIR	✅ Real-time detection	⚠️ multi-sensor fusion	⚠️ Policy learning

Table 2 provides a comparative analysis of HIRs based on different deep learning approaches. CNNs are the most efficient in terms of tradeoffs when deploying the HIRs on the edge. They provide high efficiency in terms of accuracy (84.6%-97.4%) and low latency (25-42 FPS). Transformers prove to be very effective when fusing multiple sensors with high accuracy (92.8%) but are not possible without GPU hardware, whereas DRL is adaptive learning but lacks real-world transfer and requires intensive computation.

IV. Comparative Performance Analysis: Accuracy, Latency, and Deployment Feasibility (Addressing RQ2)

This section evaluates obstacle avoidance paradigms using a unified framework. We analyze their performance against key metrics and discuss the implications for HIRO design.

A. *Standardization of Evaluation Protocol*

Systematic evaluation needs standardized data, metrics, and testbeds. The current research is fragmented in several ways:

- **Datasets:** The analyzed works show considerable fragmentation of data sources used. Around 68% of all studies employ simulation data generated via such software suites as ROS/Gazebo, Webots, or CoppeliaSim [13,16, 41]. Only 29% of all papers involve datasets with annotations for human trajectories, which poses problems regarding evaluation of social compliance. Such publicly available benchmarks as BDD100K, KITTI, or Cityscapes are used in approximately 22% of the total number of works analyzed; yet, they are designed specifically for self-driving vehicles and do not provide any indoor HIR situations necessary for evaluation [13, 27].
- **Evaluation Matrices:** Four types of metrics are used to quantitatively evaluate obstacle avoidance capabilities in the reviewed works. For evaluating detection reliability, conventional computer vision metrics are employed. Accuracy is computed as:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision is calculated according to the formula:

$$\text{Precision}=\frac{TP}{TP+FP} \tag{2}$$

Recall is calculated by the following formula:

$$\text{Recall}=\frac{TP}{TP+FN} \tag{3}$$

The F1-score is a harmonic mean of precision and recall:

$$F1=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{4}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

Avoidance Metrics: For navigation safety, collision rate (CR) quantifies the frequency of collisions:

$$CR=\frac{N_{\text{collisions}}}{N_{\text{total trials}}}\times100\% \tag{5}$$

Success rate (SR) measures the proportion of successful navigations:

$$SR=\frac{N_{\text{successful}}}{N_{\text{total trials}}}\times100\% \tag{6}$$

Path deviation quantifies the efficiency of the chosen path:

$$PD=\frac{L_{actual}-L_{optimal}}{L_{optimal}}\times 100\% \quad (7)$$

where L_{actual} is the actual travel distance and $L_{optimal}$ is the optimal travel distance [13,23, 24]. The reported collision rate is 0–15%, success rate is 85-100%, and path accuracy improvement is 5-40% over baseline approaches [14,15, 25].

- **Simulation Evaluation:** The most adopted platform is ROS/Gazebo, which is utilized by 50% of research articles because of realism, sensors integration (LiDAR, camera, IMU) and native support of machine learning using ROS [13],[16],[18],[21]. CoppeliaSim, on the other hand, is favored for research involving cobots' interaction with humans due to high fidelity kinematics, proximity and vision sensors, and simulation with MATLAB and Python [14], [25]. On the other hand, Webots is used less often due to its simplicity, wide range of sensors, and capability to integrate machine learning algorithms via Python and C++. It is worth mentioning that over 70% of the selected articles validate their proposed techniques in simulation only, whereas only 41% conduct physical experiments with robots. In addition, only 18% of the selected articles validate their techniques in dynamic environments where humans are present. Under this framework, we amalgamate findings from Table 2 (Traditional Methods) and Table 3 (Deep Learning Methods) to arrive at meaningful conclusions. The evaluation of HIR solutions is primarily done with either physics-based simulators or actual lab setups. The platforms listed are commonly employed because they can be readily adapted to perception and motion control tasks:

- **ROS/Gazebo**: most popular for realistic physics and sensor integration [13], [16].
- **CoppeliaSim**: high-fidelity, ideal for cobot-HIR studies [14].
- **Webots**: simple and ML-compatible
- **Custom indoor labs**: office corridors, crowd simulations [15], [27] .

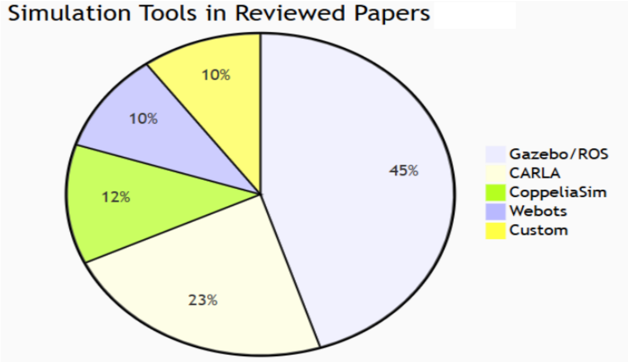

FIGURE 4. Percentage of simulation tools that used in the paper

TABLE 3. Quantitative performance improvements for obstacle avoidance

	Key Improvement	Metric	Range	Best Reported	Baseline	Reference
Traditional Methods	Collision reduction	Collision rate	60–86%	86% reduction	Standard Bug	[14,15]
	Path length reduction	Path length	1–17%	17% reduction	Standard A*	[20], [21]
	Speed improvement	Avoidance time	20–37%	37.3% faster	Standard DWA	[23, 24]
	Smoothness improvement	Trajectory smoothness	35–48%	47.9% smoother	Standard DWA	[23, 24]
	Failure reduction	Failure rate	60%	60% reduction	Standard DWA	[27]
	Path deviation	Path deviation	40%	40% less	Standard Pure Pursuit	[13]
	Travel time	Travel time	20%	20% faster	Standard VFH	[12]
Deep Learning Methods	Model size reduction	Model size	97.4%	97.4% reduction	Standard CNN	[32]
	Detection accuracy	Accuracy	84.6–96.1%	96.1% accuracy	Standalone CNN	[39]
	Multi-sensor accuracy	Accuracy	92.8%	92.8% accuracy	Traditional methods	[38]

	Navigation success	Success rate	90.2–98%	90.2% success	Baseline RL	[41]
	Crowd navigation	Collision rate	98% success	6/300 collisions	GA3C-CADRL	[25]

B. *Quantitative Performance Improvement of HIR*

The quantitative approach plays a vital role in proving the practicality of obstacle avoidance algorithms when considering their implementation for HIR. The results obtained from this analysis have been compiled and presented in Table 3. Three key parameters have been considered for each improvement observed: the measurement metric used, the degree of improvement, and the benchmark against which it has been compared. The structure facilitates an unbiased comparison of various studies on the subject matter.

The conventional approaches yield 86% reduction in collisions and 37% improvement in avoidance speed without compromising any edge capabilities, while the deep learning approaches give 96% accuracy and 97% reduction in model size at the expense of practical deployment feasibility.

C. *Research Trends*

Trend 1: *Traditional Methods Prioritize Simplicity and Predictability*

Simple and deterministic reactive techniques (e.g., VFH+ [12], Bug algorithms [14], [15], DWA [23],[24],[25],[26],[27] prioritize speed and low-cost hardware with low latency. An 86% reduction in collision rates was achieved using a Bug variant augmented with proximity, all while running on simple embedded hardware. A number are significantly reliant upon pre-mapped environments or LiDAR-SLAM integration [13], limiting generalization. Moreover, they are not well-suited to unpredictable human movement and lack social compliance mechanisms or long-term adaptation. Deliberative methods like modified Dijkstra [18] and optimized A [20],[21] provide globally optimal paths but entail greater computational expense, while dynamic re-planning suffers from local optima in complex scenarios.

Trend 2: *Lightweight CNNs Offer Edge-Compatible Intelligence*

Edge-optimized CNNs like ICNet (with network slimming) [32] and SSD MobileNetV2 [35] are very good at optimizing accuracy, size, and speed. ICNet, for instance, achieved 97% size reduction without compromising performance, executing at ~25 FPS on Jetson Nano2. Hybrid CNN-LSTM [39] models yield improved dynamic prediction (~96% accuracy at 42 FPS) but suffer from deployment challenges owing to complexity. Transformer models [38] are using self-attention to learn complex features from multi-sensor inputs and achieving 92.8% accuracy and 38 FPS, but at the cost of computational demands that hinder edge deployment that undermine edge feasibility. Only ~18% of reviewed models are edge-suitable, whereas over 59% require GPU-level resources, revealing a clear deployment bottleneck.

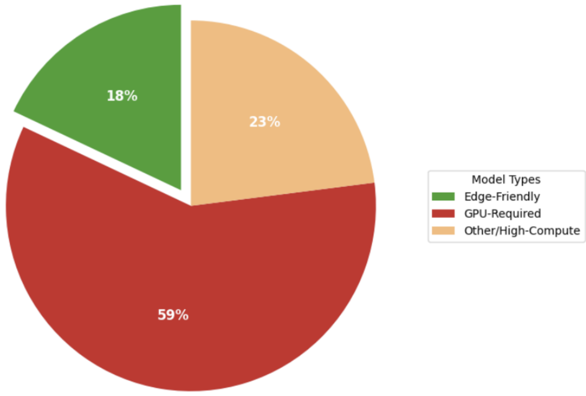

FIGURE 5. Deployment feasibility of deep learning models

Trend 3: *Reinforcement Learning Is Intelligent, But Still Behind in Practicality*

High-level decision-making capabilities are found in systems based on DRL, such as SAC + PER [29], Dueling DQN (ANOA) [30], and end-to-end monocular DRL [44]. Such models learn policies for collision avoidance through trial-and-error, even with pseudo-laser data simulated from monocular cameras [41] to serve as a low-cost alternative to LiDAR. But they are plagued by significant hindrances:

- High training time and sample inefficiency
- Poor sim-to-real transfer
- Massive memory and hardware requirements
- Lack of sensitivity to interpretability threats and safety guarantees

According to [44], end-to-end DRL struggles to generalize from simulation to real-world operation, requiring extensive fine-tuning, a severe limitation for real-time HIR deployment.

V. Identified Research Gaps and Proposed Future Directions (Addressing RQ3)

Despite the significant advances, several core challenges impede the large-scale deployment of intelligent obstacle avoidance systems in human environments. Addressing these will require progress to be synchronized across methodology, evaluation practice, and system design.

- **One of the most critical is the sim-to-real gap:** Over 70% of the examined methods are tested in simulation only, with insufficient or no real-world testing. Even when applied, these systems like end-to-end Deep Reinforcement Learning (DRL) have shown subpar performance outside simulated settings, requiring significant fine-tuning to obtain crude function [44]. This eats away at trust in their safety for such critical usage. Solutions are domain randomization [45], meta reinforcement learning[46], and self-supervised adaptation approaches [47] that enhance generalization by exposing models to diverse and noisy training environments.

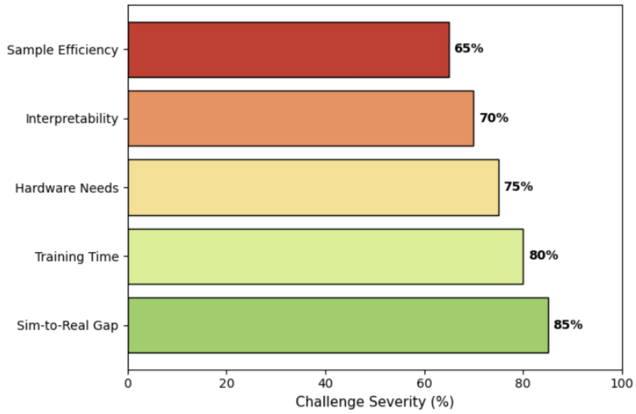

Figure 6. DRL practical limitation

- **Edge deployment bottleneck:** While deep learning offers robust perception capability, most models consume too much processing to be compatible with low-power HIRs. Validation of embedded systems is done in only 18% of methods available today. Compression techniques mentioned in Figure 8 for models (pruning[48], quantization[49], and knowledge distillation [50]) and modular architectures that allow for selective offloading to cloud resources as and when necessary, need to be the area of emphasis going forward. Hardware-software co-design, as well as leveraging specialized accelerators (e.g., TPUs, NPUs), holds the potential to balance accuracy and efficiency.

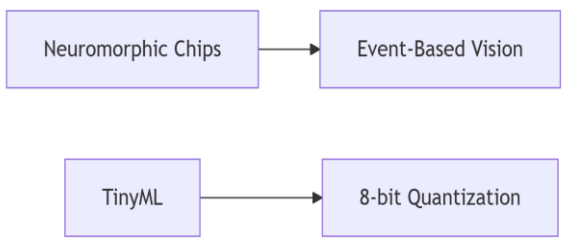

FIGURE 7. Hardware-Software co-design opportunities

- **The second important constraint is perceptual modality:** Most existing systems rely on single-sensor data (e.g., RGB cameras or LiDAR), which exposes them to occlusions, illumination variations, and sensor failures. Robust HIRs require multi-modal vision, depth, sound, IMU, and potentially touch fusion to infer context and anticipate human intent. Developing compact, yet efficient fusion networks capable of handling asynchronous and heterogeneous inputs is an open research challenge.

Future research should focus on:

(1) hybrid architectures that combine AI perception with rule-based control;
(2) domain randomization for robust sim-to-real transfer;
(3) HIR benchmarks with social compliance metrics;
(4) explainable AI for transparency; and
(5) hardware-aware model compression for edge deployment.

VI. Conclusion

This has pressed up the demand for intelligent, safe, and adaptive obstacle avoidance systems that can cover dynamic, human-shared environments. Throughout this critical review, both traditional and deep learning-based approaches have been discussed regarding their strengths and limitations in view of HIR deployments. Traditional methods, including Bug algorithms, VFH+, and DWA variants, remain a trusted baseline owing to their simplicity, real-time execution, and edge compatibility. However, they have fundamental shortcomings in chaotic, unpredictable human settings and lack adaptability or social awareness for true coexistence. Hybrid enhancements increase robustness in semi-dynamic scenarios but remain inherently rule-based and cannot generalize well in highly unstructured contexts. Deep learning has brought about a paradigm shift, allowing robots to learn robust perception and decision-making straight from raw sensory data. Consequently, this will allow lightweight CNNs to achieve both high accuracy and real-time performance on the most popular embedded platforms, such as the NVIDIA Jetson Nano, and thus are highly promising for practical HIR. Hybrid models (CNN+LSTM) introduce further improvement in temporal reasoning in crowded dynamic navigation. Advanced techniques such as transformers and DRL require substantial computational resources, GPU acceleration, and extensive training, thus becoming unfavorable for low-power, safety-critical applications. A common limitation across the literature that becomes persistent is the sim-to-real gap. More than 70% of the methods are evaluated only in simulation-for example, ROS/Gazebo and CoppeliaSim-with limited real-world validation. Also, the evaluation practice is not uniform: datasets such as BDD100K are often mismatched with indoor HIR scenarios, and social compliance metrics-meaning personal space and human comfort-are hardly included. Ultimately, the future of obstacle avoidance within human interactive robotics is not necessarily about a choice between traditional reliability and new intelligence using deep learning. Rather, the most compelling way forward is a hybrid and modular solution that fuses lightweight artificial intelligence with traditional rule-based reliability. Thus, as edge artificial intelligence research continues to advance, the focus must include better sim to real transfer, benchmarks for HIR, and socially aware navigation.

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AUTHOR CONTRIBUTIONS

Farhana Ahmed: Concept and writing - original draft, Literature search, conceptualization, drafting the methodology, concluding the research, and writing the manuscript;

Nor Hidayati Abdul Aziz: Critically reviewed, supervised, and provided feedback on the manuscript;

Rosli Besar: Critically reviewed, supervised, and provided feedback on the manuscript;

CONFLICT OF INTEREST

No conflicts of interest were disclosed.

ETHICS STATEMENTS

Ethical approval was not applicable to this research since it did not involve human participants, animals, or sensitive data.

DECLARATION OF AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During preparation of this work the author(s) used Grammarly and ChatGPT in order to improve grammar, clarity and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication. These tools were not used to generate the scholarly content of the article.

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