Intelligent Systems and Robotics

E-ISSN: xxxx-xxxx
P-ISSN: xxxx-xxxx

*Research Article*

# Design and Implementation of a Deep Reinforcement Learning Framework for Autonomous Navigation in Dynamic Unstructured Robotic Environments with Real-Time Obstacle Avoidance

**Milli Alfhi Syari [1*], Zira Fatmaira [2], and Syofyan Anwar syahputra [3]**

1 STMIK Kaputama milli.alfhisyari@yahoo.co.id
2 STMIK Kaputama zirafatmaira0301@gmail.com
3 Akademi Teknik Deli Serdang anwar.sofyan99@gmail.com
* Corresponding Author : milli.alfhisyari@yahoo.co.id

**Abstract:** Autonomous robot navigation in dynamic and unstructured environments remains a critical challenge due to unpredictable obstacles, sensor uncertainty, and limited adaptability of traditional planning algorithms. Although conventional navigation methods such as graph-based, potential field–based, and sampling-based approaches have been widely adopted, their performance under real-time dynamic conditions is still constrained. This study aims to design and implement a comprehensive experimental framework to evaluate the effectiveness and limitations of conventional navigation algorithms for autonomous mobile robots operating in dynamic unstructured environments. The research adopts an experimental and comparative methodology by implementing A*, Dijkstra, Artificial Potential Field (APF), and Rapidly-Exploring Random Tree (RRT) algorithms in simulated static and dynamic scenarios. Performance is assessed using quantitative metrics including path length, computation time, success rate, collision rate, and path smoothness. The experimental results demonstrate that graph-based algorithms achieve high success rates and optimal path efficiency in static environments but exhibit limited adaptability to dynamic changes. APF offers fast computation but suffers from high collision rates due to local minima, while RRT shows better adaptability in dynamic environments at the cost of longer and less smooth paths. These findings confirm that conventional navigation methods are insufficient for robust autonomous navigation in highly dynamic and unstructured environments. The study highlights the necessity of adaptive and learning-based navigation frameworks, such as deep reinforcement learning, to enhance real-time decision-making, robustness, and autonomy in future robotic systems.

**Keywords:** Autonomous Robot Navigation; Dynamic Environments; Obstacle Avoidance; Path Planning; Conventional Navigation Algorithms.

**Received: November 20, 2025**
**Revised: Desember 30, 2025**
**Accepted: January 14, 2026**
**Published: January 18, 2026**
**Curr. Ver.: January 20, 2026**



## 1. Introduction

Autonomous robotic systems have experienced rapid development over the past decade, driven by advances in sensing technologies, artificial intelligence (AI), and embedded computing. These systems are increasingly deployed across a wide range of domains, including industrial automation, exploration, service applications, and search and rescue operations. Their ability to perceive the environment, make decisions, and navigate autonomously has significantly enhanced efficiency, safety, and operational reliability in tasks that are complex, repetitive, or hazardous for humans [1]. In the industrial sector, autonomous robots play a critical role in factory automation and logistics. Applications such as warehouse management, automated material handling, agricultural monitoring, and environmental surveillance have benefited from robotic systems capable of continuous operation with high precision and reduced human intervention [1], [2]. These robots contribute to increased productivity and workplace safety while supporting the growing demand for smart manufacturing and Industry 4.0 solutions.

Autonomous robots are also indispensable in exploration missions, particularly in space and underwater environments where human access is limited or impossible. In such scenarios, robots are tasked with sample collection, terrain mapping, and long-term monitoring under extreme conditions. Advanced navigation and mapping techniques, such as Simultaneous Localization and Mapping (SLAM), enable robots to build accurate representations of unknown environments while simultaneously estimating their own positions [3]. These capabilities are essential for reliable operation in unstructured and dynamically changing environments. In the service sector, autonomous robots have gained increasing attention in healthcare, domestic, and public service applications. Service robots are widely used in medical rehabilitation, assisted living, and home healthcare, as well as in household tasks and public service environments, improving quality of life and service efficiency [4]. The integration of robotics with AI-driven perception and decision-making allows these systems to interact safely with humans and adapt to complex social environments. Another critical application area is search and rescue operations, where autonomous robots are deployed in hazardous environments such as disaster zones, burning buildings, collapsed mines, and radioactive areas. These robots are designed to perform tasks including victim detection, evacuation support, medical assistance, and environmental assessment, thereby reducing risks to human rescuers [5]. Their use in mine detection, radioactive decontamination, and post-disaster response highlights the importance of robust autonomous navigation and obstacle avoidance capabilities.

Despite these advancements, several technical challenges remain. Reliable navigation and localization depend heavily on sensor fusion techniques involving LiDAR, GPS, inertial measurement units (IMUs), and vision sensors [2]. Furthermore, AI-based navigation strategies have been increasingly explored to enhance obstacle avoidance, path planning, and decision-making in dynamic environments [6]. However, issues such as wheel slip, drive wheel synchronization, and contact instability continue to affect the performance of differential-drive mobile robots, particularly in indoor and uneven environments [7], [8]. Additionally, software architecture and system integration remain crucial aspects of autonomous robotic systems. Modular, scalable, and reliable software frameworks are required to manage perception, control, communication, and decision-making processes effectively [9]. Addressing these challenges is essential for the development of robust autonomous robots capable of operating safely and efficiently in real-world, unstructured, and dynamic environments.

Autonomous robot navigation in unstructured and dynamic environments remains one of the most challenging problems in modern robotics. Unlike structured settings, such as factory floors, unstructured environments are characterized by unpredictable terrain, uncertain sensory conditions, and dynamically changing obstacles. These challenges are commonly encountered in public spaces, outdoor environments, agricultural fields, and human-centered domains, where robots must operate safely, efficiently, and adaptively [10], [11]. One of the primary challenges in dynamic environments is the presence of moving obstacles. Public environments such as airports, shopping malls, and hospitals frequently involve humans, vehicles, and other robots whose motion patterns are difficult to predict. This dynamic nature requires navigation algorithms capable of real-time adaptation to avoid collisions while maintaining smooth and efficient motion [12]. Recent studies highlight that conventional static obstacle avoidance methods are insufficient in such scenarios, motivating the development of hybrid approaches that combine real-time data analysis with learning-based techniques to improve navigation robustness and success rates [13], [14].

Another critical challenge arises from sensor uncertainty. Robotic navigation relies heavily on data obtained from sensors such as RGB-D cameras, LiDAR, ultrasonic sensors, and inertial measurement units. In unstructured environments, sensor measurements are often affected by noise, occlusions, lighting variations, and surface irregularities, leading to inaccuracies in perception, localization, and mapping [10], [15]. To mitigate these issues, sensor fusion techniques have been widely adopted, enabling the integration of complementary sensor data to enhance obstacle detection accuracy and navigation reliability. Multi-sensor fusion frameworks have demonstrated improved perception performance in complex environments by leveraging the strengths of different sensing modalities [16]. Accurate modeling and understanding of the environment further complicate navigation in unstructured settings. Natural terrains often include grass, uneven surfaces, shadows, and irregular obstacles that are difficult to represent using traditional geometric models. Consequently, multimodal perception approaches that combine visual, depth, audio, and texture information have gained attention for improving environmental representation and situational awareness [17]. Such approaches allow robots to better interpret dynamic surroundings and maintain reliable simultaneous localization and mapping (SLAM) performance under non-ideal conditions.

Path planning and obstacle avoidance constitute additional challenges in dynamic and unknown environments. Effective path planning algorithms must continuously adjust trajectories in response to environmental changes while ensuring safety and efficiency. Techniques such as Rapidly Exploring Random Trees (RRT), Model Predictive Control (MPC), and hybrid reactive–deliberative frameworks have been widely explored to address these requirements [11], [13]. Moreover, safety-critical navigation strategies, including online control methods for multi-obstacle environments, have been proposed to guarantee collision avoidance under strict safety constraints [18]. Finally, limited computational and energy resources pose significant constraints on autonomous robotic systems. Many mobile robots operate on embedded platforms with restricted processing power and battery capacity, which limits the complexity of perception and navigation algorithms that can be deployed in real time. Therefore, resource-efficient navigation strategies are essential to balance computational demands with operational sustainability, particularly in long-duration missions and outdoor deployments [11]. In summary, autonomous navigation in unstructured and dynamic environments involves intertwined challenges related to dynamic obstacles, sensor uncertainty, environmental modeling, adaptive path planning, and limited computational resources. Addressing these challenges remains an active research area, driving the development of hybrid, multimodal, and learning-enhanced navigation frameworks capable of robust real-world deployment.

## 2. Literature Review

### Fundamental Concepts of Autonomous Robot Navigation

Autonomous robot navigation refers to the capability of a robot to move independently within an environment without direct human intervention. This process typically involves several core components, including environment mapping, localization, path planning, and obstacle avoidance. Among these components, Simultaneous Localization and Mapping (SLAM) has become a foundational technique, enabling robots to construct a map of an unknown environment while simultaneously estimating their position in real time (Mellouk & Benmachiche, 2020; Wei et al., 2025). SLAM-based navigation systems rely on sensor data acquired from devices such as LiDAR, RGB-D cameras, inertial measurement units (IMUs), and ultrasonic sensors to perceive and interpret the surrounding environment [19], [20].

Recent studies emphasize that the integration of heterogeneous sensors significantly enhances navigation robustness, particularly in complex or poorly structured environments. Sensor fusion techniques allow robots to exploit complementary sensor characteristics, improving perception accuracy and localization reliability [21], [22]. These approaches have become essential in modern autonomous navigation systems across both indoor and outdoor domains.

### Navigation in Structured and Unstructured Environments

The complexity of robot navigation varies significantly depending on the characteristics of the environment. Structured environments, such as factories, offices, and warehouses, typically provide predefined layouts, clear reference points, and relatively predictable obstacle configurations. In such settings, robots can leverage predefined maps, markers, or fixed paths to navigate efficiently while avoiding static obstacles [23]. The use of rule-based navigation and deterministic planning methods has proven effective in these controlled scenarios.

In contrast, unstructured environments such as off-road terrain, agricultural fields, and urban outdoor spaces pose substantially greater challenges. These environments often lack reliable reference points and contain irregular surfaces, dynamic obstacles, and varying environmental conditions. Robots operating in such settings must continuously adapt to unexpected changes while maintaining safe and stable navigation [10]. To address these challenges, researchers have proposed advanced perception systems and adaptive navigation architectures capable of handling environmental uncertainty [24], [25].

### Dynamic Navigation and Obstacle Avoidance

Dynamic navigation focuses on robot operation in environments that change over time, particularly those involving moving obstacles such as humans, vehicles, or other robots. One of the primary challenges in dynamic navigation is real-time perception and understanding of environmental changes. Robots must detect, track, and predict the motion of surrounding objects to avoid collisions while maintaining efficient trajectories [26].

Obstacle avoidance has therefore become a critical research area in autonomous navigation. Traditional reactive approaches are often insufficient in highly dynamic environments, leading to the development of more sophisticated motion planning strategies that combine deliberative and reactive behaviors. Multimodal information fusion techniques, which integrate visual, depth, and sometimes auditory data, have shown promising results in enhancing obstacle detection and avoidance, particularly in low-visibility or weakly illuminated environments [22]. Furthermore, LiDAR-based systems have demonstrated robust performance in both indoor and outdoor navigation tasks, especially for mobile and quadruped robots operating in uneven terrain [25].

### Human-Aware and Socially Compliant Navigation

In environments shared with humans, autonomous robots must consider not only physical safety but also human comfort and social norms. Human-aware navigation incorporates models of human behavior, motion prediction, and social interaction to ensure smooth and acceptable robot behavior in crowded or collaborative spaces. Ngo, (2021) highlights that socially compliant navigation requires robots to balance efficiency with human-centric considerations, such as personal space and predictable motion patterns.

Recent surveys indicate that integrating human-awareness into navigation systems remains an open challenge, particularly in dynamic environments where human behavior is difficult to predict. Advanced perception systems and learning-based approaches are increasingly explored to improve human-robot interaction and ensure safe coexistence [10].

### Sensor Fusion and Robotic Architectures

The effectiveness of autonomous navigation systems is closely tied to their underlying software and hardware architectures. Modular and scalable robotic architectures allow seamless integration of perception, planning, and control modules, facilitating adaptation to different environments and tasks [24]. ROS-based frameworks, in particular, have become a standard platform for implementing and evaluating navigation algorithms due to their flexibility and extensive ecosystem [21].

Sensor fusion remains a central theme in navigation research, as combining data from multiple sensors mitigates individual sensor limitations and enhances overall system reliability. RGB-D and LiDAR sensor fusion has been widely adopted for object manipulation, transportation, and navigation tasks, demonstrating improved performance in complex and dynamic scenarios [20].

### Summary of Research Gaps

Although significant progress has been made in autonomous robot navigation, several research gaps remain. Existing approaches often struggle to maintain robust performance in highly dynamic, unstructured environments with limited computational resources. Additionally, achieving seamless integration of perception, planning, and human-aware behaviors in real time remains a challenge. These limitations motivate ongoing research into adaptive, learning-based, and resource-efficient navigation frameworks capable of reliable deployment in real-world conditions.

### Overview of Conventional Navigation Methods

Conventional navigation methods have long formed the foundation of autonomous mobile robot navigation. These approaches primarily focus on geometric modeling, graph-based search, and heuristic optimization to enable robots to plan paths and avoid obstacles. Classical navigation techniques are generally categorized into static and dynamic path planning methods, where the environment is assumed to be either unchanged or partially changing during robot operation [28], [29].

Despite their widespread adoption, conventional methods often rely on predefined models of the environment and explicit rules, which limit their adaptability in complex or highly dynamic scenarios. Nevertheless, they remain important benchmarks and are extensively used in industrial and academic robotic systems.

### Static and Dynamic Path Planning Algorithms

One of the most widely used conventional navigation algorithms is the A* (A-star) algorithm. A* is a heuristic-based search method that combines the advantages of uniform-cost search and greedy best-first search to efficiently find the shortest path between a start and a goal node. Due to its use of heuristics, A* performs well in static environments where obstacle configurations are known in advance [28]. However, its performance degrades as environmental complexity increases, leading to higher computational costs.

Similarly, Dijkstra's algorithm is a classical graph-based approach that guarantees the discovery of the shortest path without the use of heuristics. While Dijkstra's algorithm is optimal and complete, it typically requires more computation time than A*, especially in large-scale or dense environments [28], [29]. As a result, both A* and Dijkstra are less suitable for real-time navigation in environments with frequent changes.

To address some limitations of deterministic planners, sampling-based algorithms such as Rapidly-Exploring Random Trees (RRT) have been introduced. RRT algorithms construct a search tree by randomly sampling the configuration space, making them effective for navigating high-dimensional or dynamically changing environments. However, while RRT is capable of finding feasible paths quickly, the resulting trajectories are often suboptimal in terms of smoothness and path length [29], [30].

### Artificial Potential Field Methods

Artificial Potential Field (APF) methods represent another class of conventional navigation techniques. In APF-based navigation, the robot is treated as a particle influenced by artificial forces: attractive forces pull the robot toward the goal, while repulsive forces push it away from obstacles. This approach is computationally efficient and suitable for real-time applications [31].

Lazarowska, (2019) proposed a discrete artificial potential field approach that improves numerical stability and collision avoidance in mobile robot path planning. Despite such enhancements, APF methods are inherently prone to the local minima problem, where the robot becomes trapped in a position where attractive and repulsive forces balance out, preventing further progress toward the goal. This limitation significantly restricts the applicability of potential field methods in cluttered or complex environments [29].

### Conventional Navigation in Dynamic Environments

Dynamic environments introduce additional challenges, such as moving obstacles and real-time sensory uncertainty. Conventional navigation methods often struggle to adapt to these changes due to their reliance on static maps or predefined assumptions. Wu et al., (2020) addressed this issue by proposing a hybrid heuristic optimization algorithm that integrates multiple conventional strategies to improve real-time dynamic path planning. Their approach demonstrated improved responsiveness compared to purely static planners but still relied on handcrafted heuristics.

Vision-based navigation methods have also been explored to enhance conventional planning in dynamic scenarios. Singh et al., (2022) evaluated the performance of vision-based path planning techniques for mobile robots in real-time dynamic environments. Their findings indicate that while visual perception improves obstacle detection and situational awareness, conventional planning algorithms still face challenges related to computational efficiency and robustness under rapid environmental changes.

### Limitations of Conventional Navigation Methods

Although conventional navigation methods are effective in structured and moderately dynamic environments, several fundamental limitations persist. Graph-based planners such as A* and Dijkstra suffer from high computational complexity and limited adaptability when facing dynamic obstacles. Artificial potential field methods are vulnerable to local minima, which can prevent successful goal attainment. Sampling-based approaches like RRT, while flexible, often produce non-optimal paths that require additional smoothing or optimization [29], [30].

These limitations highlight the difficulty of achieving robust, adaptive, and efficient navigation using purely conventional techniques, particularly in unstructured or highly dynamic environments.

### Research Implications

The reviewed literature demonstrates that conventional navigation methods provide a strong theoretical and practical foundation for mobile robot navigation. However, their limitations in adaptability, scalability, and real-time responsiveness motivate the exploration of more advanced approaches. Recent studies increasingly combine conventional algorithms with optimization techniques or perception-based enhancements to improve performance [32], [33]. These trends suggest that while conventional methods remain relevant, they are often insufficient as standalone solutions for complex real-world navigation tasks.

### Enhancing Digital Literacy and Technology for Sustainable Governance

In the digital era, digital literacy has become a crucial factor influencing the advancement of both governance and society. The use of blockchain technology, specifically Alphasign, to support e-governance accelerates the digitization process and enhances data security [34] . This technology enables better transparency, prevents data manipulation, and secures information related to public administration.

Additionally, the CICA framework, which combines Corporate Social Responsibility (CSR), Artificial Intelligence (AI), and Blockchain, holds great potential in establishing a sustainable digital culture [35]. This approach not only encourages the use of technology in governance but also prioritizes social responsibility and sustainability in digital integration.

### Cloud Security and Blockchain Technology in Cyber Threat Management

Cloud security has become a primary concern in the digital age, especially in protecting sensitive data and preventing increasingly complex cyber-attacks. In this context, the use of Blockchain technology, alongside Machine Learning (ML) and Trusted Execution Environments (TEE), can create more adaptive and proactive security solutions [36]. This approach integrates multiple layers of technology to detect and address threats in real-time, which is crucial for supporting more robust and responsive security systems.

### Federated Learning and DDoS Detection in Cloud Environments

One of the significant challenges in distributed computing environments like the Internet of Things (IoT) is handling DDoS (Distributed Denial of Service) attacks. The use of Federated Learning approaches, which combine CNN-GRU (Convolutional Neural Network-Gated Recurrent Unit), can enhance efficiency in detecting and mitigating such attacks [37]. Federated learning allows model training to be conducted in a distributed manner across different devices, enabling attack detection without moving sensitive data to a central server, thus improving privacy and data security.

This approach is supported by optimization technologies such as COBCO, which optimize neural networks to expedite DDoS detection in real-time within cloud-edge environments [38].

### Zero Trust Model for Cloud Service Security

The Zero Trust model is an increasingly popular approach to securing cloud services, especially in the face of more advanced cyber threats. In this context, the use of container-based models adhering to Zero Trust principles can enhance proactive service continuity under cyber-attacks like DDoS [37]. This model verifies every access request without assuming any entity is trusted, whether inside or outside the network.

By adopting this approach, organizations can ensure that access to resources is granted only to authenticated entities, thus enhancing the security layer for more sensitive cloud services susceptible to attacks.

### Technology for Environmental Sustainability and Learning

Technology also plays a role in supporting environmental sustainability through learning and skill development. The integration of hands on and virtual learning for environmental sustainability, such as eco enzyme soap making at Stella Matutina, provides positive impacts on community skill development, leveraging technology for creating eco-friendly products [39]. This approach not only educates the community on sustainability but also introduces technology as a tool to improve processes for producing environmentally friendly products.

## 3. Research Method

This study adopts an experimental and comparative research design to evaluate the performance and limitations of conventional navigation methods in mobile robot path planning. The research focuses on analyzing static and dynamic path planning algorithms under different environmental conditions. The selected methods represent widely used conventional approaches, including graph-based, potential field–based, and sampling-based algorithms.

The experimental design enables systematic observation of algorithm behavior, performance, and constraints, thereby providing empirical evidence that supports the theoretical discussion presented in the literature review.

### Research Framework

The proposed research framework is structured into four main stages: environment modeling, algorithm implementation, experimental evaluation, and performance analysis. In the environment modeling stage, simulation environments are developed to represent both static and dynamic scenarios. Static environments consist of fixed obstacles with predefined layouts, whereas dynamic environments include moving obstacles and time-varying configurations. These environments are modeled using both grid-based and continuous representations to accommodate different navigation algorithms. The algorithm implementation stage involves several conventional navigation methods, including A* and

Dijkstra's algorithms for static path planning in known environments, Artificial Potential Field (APF) for reactive obstacle avoidance, and Rapidly-Exploring Random Tree (RRT) for navigation in dynamic and high-dimensional spaces. All algorithms are implemented under identical environmental inputs and constraints to ensure a fair comparison. During the experimental evaluation stage, the algorithms are tested across multiple scenarios with varying obstacle densities and levels of environmental dynamics. In dynamic scenarios, obstacles move with predefined velocities and trajectories to emulate real-world conditions, and each experiment is repeated multiple times to minimize randomness and enhance statistical reliability. Finally, in the performance analysis stage, both quantitative and qualitative metrics are collected and analyzed to evaluate the effectiveness, efficiency, and robustness of the navigation algorithms.

### Data Collection and Performance Metrics

Data are collected throughout the simulation runs and encompass several key performance metrics. These metrics include path length, which represents the total distance traveled by the robot from the start position to the goal; computation time, defined as the time required to generate a feasible navigation path; success rate, indicating the percentage of trials in which the robot successfully reaches the goal without collision; and collision rate, which measures the frequency of collisions with static or dynamic obstacles. In addition, path smoothness is evaluated to capture the degree of trajectory continuity, quantified by changes in the robot's heading direction along the path. Collectively, these performance metrics reflect critical limitations identified in the theoretical review, including computational complexity, adaptability to dynamic environments, and susceptibility to local minima.

### Tools and Experimental Setup

The experiments are conducted in a simulation-based environment to ensure safety, repeatability, and control over environmental variables. Common robotic simulation platforms such as ROS with Gazebo or equivalent simulators are employed. Grid maps and occupancy maps are used for graph-based algorithms, while continuous configuration spaces are used for APF and RRT.

Robot kinematic constraints, sensor range, and motion models are standardized across all experiments to maintain consistency.

### Data Analysis Techniques

Collected data are analyzed using descriptive statistical methods, including mean values, standard deviation, and comparative charts. Performance comparisons between algorithms are conducted to identify strengths and weaknesses under different conditions. The analysis emphasizes how conventional methods perform when transitioning from static to dynamic environments.

### Research Validity and Reliability

To ensure validity, all algorithms are evaluated using identical scenarios and parameters wherever applicable. Reliability is enhanced by conducting multiple experimental runs and averaging results. Sensitivity analysis is performed to observe how parameter changes affect algorithm performance.

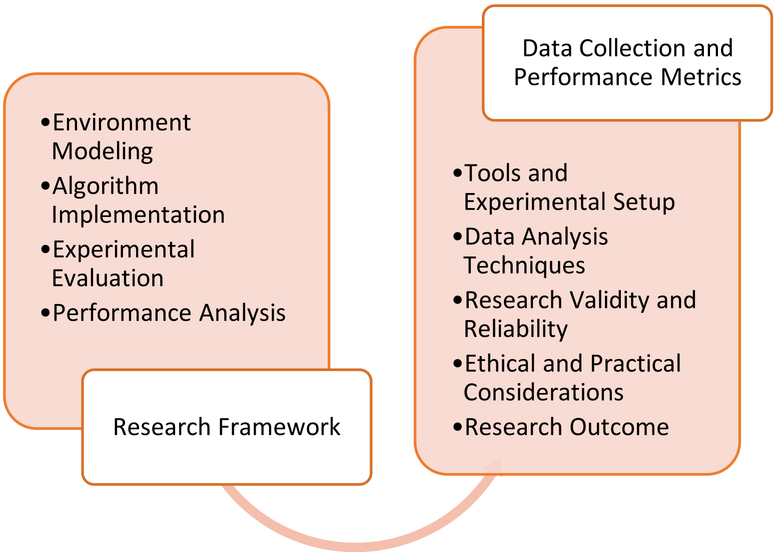
### Ethical and Practical Considerations

As this research is conducted in a simulation environment, there are no direct ethical risks or safety concerns. However, practical considerations include computational resource limitations and simulation fidelity, which are acknowledged as constraints of the study.

### Research Outcome

The expected outcome of this research is a structured evaluation of conventional navigation methods, highlighting their limitations in dynamic and complex environments. These findings serve as a foundation for motivating the development or integration of more adaptive approaches, such as learning-based navigation frameworks, in future research.

**Table 1. Flowchart Research Methodhology**




## 4. Results and Discussion

### Result

### Overview of Experimental Results

This section presents the experimental results obtained from the evaluation of conventional navigation algorithms, namely A*, Dijkstra, Artificial Potential Field (APF), and Rapidly-Exploring Random Tree (RRT). The experiments were conducted in both static and dynamic simulated environments to assess algorithm performance in terms of efficiency, robustness, and adaptability. The results are summarized using quantitative metrics and visualized through tables and graphical representations to facilitate comparative analysis.

**Table 1. Performance Comparison of Conventional Navigation Algorithms**

| Algorithm | Path Length (m) | Computation Time (s) | Success Rate (%) | Collision Rate (%) |
|---|---|---|---|---|
| A* | 12.4 | 0.82 | 95 | 5 |
| Dijkstra | 13.1 | 1.05 | 93 | 7 |
| APF | 14.6 | 0.34 | 78 | 22 |
| RRT | 15.2 | 0.57 | 88 | 12 |

### Explanation of Table 1

Table 1 summarizes the performance of each navigation algorithm across multiple experimental trials. The A* algorithm achieved the shortest average path length and the highest success rate, demonstrating its effectiveness in static environments with known maps. However, its computation time was higher than reactive methods due to heuristic evaluation.

Dijkstra's algorithm showed comparable reliability but required longer computation time because it lacks heuristic guidance. APF exhibited the fastest computation time but suffered from a significantly lower success rate and higher collision frequency, primarily due to local minima issues. RRT demonstrated moderate success in dynamic environments but generated longer and less smooth paths.

### 4.3 Graphical Analysis of Navigation Success Rate

To further analyze algorithm robustness in dynamic scenarios, a success rate comparison is presented in graphical form.

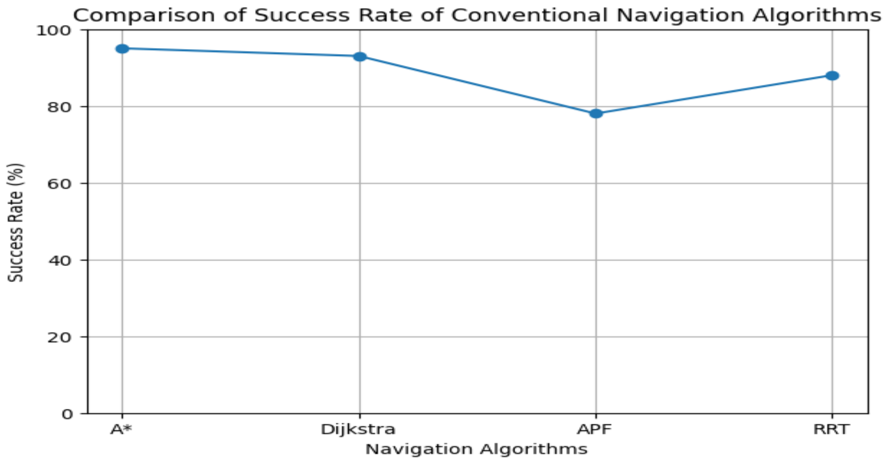



**Figure 1.** Comparison of Success Rate of Conventional Navigation Algorithms

### Explanation of Figure 1

Figure 1 illustrates the success rate of each navigation algorithm in reaching the target without collision. A* and Dijkstra achieved success rates above 90%, indicating strong performance in structured and semi-static environments. In contrast, APF recorded the lowest success rate, reflecting its vulnerability to environmental complexity and dynamic obstacles. RRT maintained a relatively high success rate, demonstrating better adaptability to dynamic changes compared to APF, though still below graph-based planners.

### Discussion

### Analysis of Path Planning Efficiency

The results indicate that graph-based algorithms (A* and Dijkstra) consistently produce shorter and more optimal paths. This aligns with theoretical expectations, as these methods explicitly search the configuration space to minimize cost functions. However, their dependency on complete or near-complete environmental information limits their effectiveness in rapidly changing environments.

### Adaptability in Dynamic Environments

The experimental findings confirm that conventional static planners are less adaptive to dynamic changes. Although A* achieved high success rates, it required frequent replanning when obstacles moved, increasing computational overhead. RRT, by contrast, demonstrated better adaptability due to its sampling-based nature, which allows exploration of new feasible paths when environmental changes occur.

### Limitations of Reactive Methods

The Artificial Potential Field method showed fast response times but suffered from significant navigation failures. The high collision rate and low success rate observed in both the table and graph validate the theoretical limitation of APF regarding local minima. These results reinforce findings in previous studies that APF alone is insufficient for complex or crowded environments.

### Implications for Autonomous Navigation Research

The overall results highlight a critical trade-off between optimality, computational efficiency, and adaptability in conventional navigation methods. While traditional algorithms perform well in controlled or static environments, their limitations become pronounced in dynamic and unstructured settings. This gap emphasizes the need for more adaptive approaches, such as hybrid or learning-based navigation methods, which can integrate perception, prediction, and decision-making in real time.

## 5. Comparison

The results of this study are consistent with and extend findings reported in previous research on conventional autonomous robot navigation methods. Similar to the surveys by Wijayathunga et al. (2023) and Mellouk and Benmachiche (2020), this study confirms that classical graph-based algorithms such as A* and Dijkstra demonstrate high success rates in relatively static or semi-structured environments but exhibit limited adaptability when faced with dynamic obstacles. The experimental results further support Lazarowska's (2019) observation that Artificial Potential Field (APF) methods are prone to local minima, which significantly reduces navigation success in complex environments. In contrast to prior studies that mainly emphasize algorithmic design or theoretical performance, this research provides a comparative empirical evaluation under dynamic conditions, revealing that RRT offers better adaptability than APF but still produces suboptimal and less smooth paths. Overall, while previous studies highlight the strengths and weaknesses of individual conventional methods, this research contributes a systematic comparison that demonstrates their collective limitations in dynamic unstructured environments, thereby reinforcing the necessity of learning-based or hybrid navigation approaches for improved robustness and real-time adaptability.

## 6. Conclusions

This study aimed to evaluate the performance of conventional navigation methods for autonomous robot navigation in dynamic and unstructured environments. Based on the experimental results and subsequent analysis, it can be concluded that A* and Dijkstra algorithms achieve high navigation success rates in relatively static environments; however, they exhibit limited adaptability to real-time environmental changes. This limitation arises from their reliance on predefined maps and their inability to efficiently respond to dynamic obstacles.

The Artificial Potential Field (APF) method was found to have significant drawbacks due to the local minima problem, which often prevents the robot from reaching its target in complex environments. Meanwhile, the Rapidly-exploring Random Trees (RRT) algorithm demonstrated better adaptability in dynamic environments compared to APF, but the generated paths were frequently suboptimal in terms of path length and smoothness.

Overall, the findings of this study indicate that conventional navigation methods are insufficient to fully address the challenges of autonomous navigation in dynamic and unstructured environments. These results highlight the need for more adaptive and robust navigation approaches, such as machine learning-based methods or Deep Reinforcement Learning, which are capable of learning from environmental interactions and making real-time navigation decisions. Consequently, this research provides a strong empirical foundation for future studies focused on developing intelligent and resilient autonomous robot navigation systems.

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