Computers, Materials & Continua

Tech Science Press

https://doi.org/10.32604/cmc.2026.082572

ARTICLE

Generative World Modeling for Risk-Aware Autonomous UAV Navigation in Dynamic Traffic Networks

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Received: 18 March 2026; Accepted: 14 May 2026; Published: 23 July 2026

ABSTRACT: Unmanned Aerial Vehicles (UAVs) are finding more and more applications in logistics, surveillance, and other operations at a large scale. However, autonomous navigation in dynamic traffic situations is not an easy task due to limited energy, moving obstacles, and inter-agent interactions. The proposed paper can be discussed as a Generative World Modeling (GWM) framework of risk-focused UAV navigation in the dynamic traffic network. This paper proposes a GWM framework for risk-aware UAV navigation in dynamic traffic networks. The proposed design incorporates three key elements; a generative world model for predicting future environmental conditions, a diffusion-based trajectory-generation component that generates multiple possible paths, and a risk-aware decision-making component that selects trajectories based on energy use, collision avoidance, and mission criteria. The framework is also extended to the case of a multi-UAV swarm, where a coordinated swarm is facilitated by shared representations in the latent space to alleviate potential conflicts. The experimental analysis of real-world-inspired UAV trajectory data indicates that the proposed GWM framework outperforms the classical, reinforcement-based, and conflict-aware baseline approaches across a range of performance metrics, including mission success rate, delivery time, energy cost, safety, and path efficiency. The findings indicate that with risk-sensitive and generative prediction, autonomous UAV missions should be more robust, effective, and secure in uncertain, complex environments.

KEYWORDS: Unmanned aerial vehicles; generative AI; autonomous navigation; risk-aware decision; trajectory planning; swarm coordination

1 Introduction

Unmanned Aerial Vehicles (UAVs) are a new technology that could be applied to logistics, surveillance, environmental scanning, and smart city management. They are incapable of compromise because of their plasticity in operation, operational speed, and the capacity to mount complex ground systems to enable real-time situation-awareness and independent security mission operations [1]. The strategic role of UAVs in the contemporary infrastructural context has also been ascertained due to the blistering trend of e-commerce, growing popularity of last-mile marketing, and the necessity to provide a secure disaster management [2,3]. Despite such benefits, the autonomous UAV navigation in the dynamic uncertainties is a major challenge, as a result of power constraints, traffic uncertainty, temporary obstacles, and inter-agent collisions.

The majority of conventional navigation and path-planning methods for UAV systems are deterministic or reactive [4]. Despite these approaches working effectively in controlled or stationary settings, in real-world scenarios where traffic networks and weather conditions, along with roadblocks, are in a continuous state of flux, critical shortcomings are noted [5]. Deterministic algorithms cannot forecast the future, and RL-based methods can be expensive to train and may not generalize to non-in-distribution environments. Thus, real-time UAVs are more prone to mission failure, energy wastage, and collisions, particularly in large urban traffic systems.

Generative Artificial Intelligence (GAI) developed over the last few years presents an opportunity to eliminate these barriers. Generative models that can train on complex environmental distributions using diffusion models, transformer-based networks, and world models can generate plausible future scenarios. UAVs can evolve into imagination-driven models, rather than reactive path navigation, by introducing these models into the UAV navigation system [6]. By predicting potential future environmental conditions prior to taking action, the UAVs can calculate alternative courses of action when faced with uncertainty, account for energy consumption, and take the initiative to avoid collisions, thereby increasing mission success rates and operational safety.

This paper proposes a GWM approach for risk-aware UAV navigation in dynamic traffic networks. The system integrates probabilistic future model prediction, trajectory generation through diffusion, and risk-aware state search to support the anticipatory, adaptive, and risk-averse navigation. It is also generalizable to multi-UAV swarm cases, where the collective latent space serves as a representation of cooperative decision-making, unlike classical, reinforcement-based, and traditional world-modeling methods. The most important conclusions of the research are as follows:

- This study develops a GWM system that enables UAVs to anticipate unexpected traffic conditions, features, and environmental turbulence, thereby enabling proactive, imagination-based maneuvering.
- The proposed work presents diffusion-based trajectory synthesis that generates multiple possible trajectories that satisfy dynamic constraints and enhance their strength and flexibility during operation in unpredictable environments.
- This study presents a risk-aware decision-making process that accounts for potential paths in energy consumption and safety, thereby minimizing collision risk and optimizing operational efficiency.
- The framework enables coordination of multi-agent and swarms by using common latent spaces to support joint decision-making among multiple UAVs, thereby offering adaptive coordination of swarms in complex environments.
- To make the comparisons of the efficiency of the proposed framework, a high level of simulation-oriented validation is conducted within the frame of the actual-life dynamic traffic networks, which happens to raise the success rates of the missions, the efficiency of energy consumption, as well as the safety of the operations significantly.

The remainder of the paper is structured as follows: Section 2 examines the literature and the strategies available to date in UAV navigation. Section 3 presents the system model and formulation of the problem. Section 4 explains the proposed GWM framework, including trajectory generation and risk-aware decision making. Section 5 contains the description of the simulation and experimental assessment. The results and the comparative analysis are discussed in Section 6. Lastly, Section 7 concludes and outlines directions for future work.

2 Related Work

The growing need for aerial delivery, surveillance, and environmental monitoring has driven the development of autonomous UAV navigation systems. Recent research [7] identifies shortcomings of reactive planning approaches for planning tasks under changing traffic and moving obstacles, and, as noted in [8], deterministic planning methods frequently fail in the presence of uncertainty, such as changing weather and unpredictable agent actions. Other studies on multi-agent UAV systems have investigated the problem of coordinated flight among several vehicles. The collision-free navigation of small groups of UAVs through conflict-aware planning methods described in [9] is guaranteed; however, the computational complexity of conflict-free navigation increases exponentially with the size of the swarm, making real-time operation difficult. The heuristic conflict-avoidance and task-allocation schemes are more scalable, but still rely on existing knowledge of the environment, and, as stated in [10], most classical methods for multi-agent systems do not effectively address uncertainty modeling or risk-aware decision-making.

To address these aspects, artificial intelligence, specifically Reinforcement Learning (RL), has been employed. Research in [11,12] applies RL to adapt UAV navigation to changing conditions and traffic interest. Nonetheless, according to [13], RL requires extensive training and may perform poorly out-of-distribution, and even the policies are typically shortsighted and do not model the environment predictively. Generative AI has also recently become an effective predictive modeler in robotics and autonomous systems. World models [14] and diffusion models [15] can generate plausible sequences of future states, enabling planning under uncertainty. In autonomous driving [16], robot manipulation, and UAV swarms [17], generative models have been shown to support foresight and joint decision-making. Although these innovations have been made, few models integrate generative models with risk-aware trajectory planning for UAVs in dynamic traffic networks under energy constraints.

The current developments in generative artificial intelligence have had a major impact on predictive-based modeling and decision-making in autonomous systems. Diffusion-based models are shown to be successful at generating diverse future paths in the presence of uncertainty; meanwhile, Ref. [18] identifies transformer-based world models as capable of modeling various temporal dependencies in predictive planning. Correspondingly, recent studies [19] highlight the power of generative models in autonomous driving and robotic navigation, where it is necessary to consider multiple possible future courses of action to operate safely and efficiently. Additionally, there is the issue of integrating generative modeling with decision-making models to enable foresight-based planning rather than reactive or deterministic methods, as presented in [20].

Moreover, the authors in [21] highlight the use of probabilistic modeling on the coordination of the multi-agent systems, especially in dynamic and safety-critical settings. These advancements suggest increased interest in adopting the synergistic approach to generative prediction and adaptive control for real-time navigation. However, they are still using them a little for UAV navigation in moving traffic networks despite these advancements. Specifically, predictive modeling and the effective application of risk-aware decision-making based on energy and safety constraints are not sufficiently incorporated into most existing methods. This gap presents an opportunity to develop common paradigms integrating generative modeling, trajectory synthesis, and risk-aware optimization to enhance resilient UAV navigation.

The literature review demonstrates that there are several gaps in UAV navigation studies. The classical and reinforcement learning-based approaches tend to be reactive, whereas multi-agent approaches often lack explicit consideration of uncertainty or probabilistic safety. Even though generative models offer better predictive performance, the majority of studies hitherto have not combined this with risk-conscious trajectory analysis under operational constraints. Similarly, existing methods for multi-UAV coordination enhance conflict avoidance but seldom provide cooperative, generative planning with energy-aware decisions. The presented GWM framework can overcome these constraints by combining probabilistic environment modeling, diffusion-based trajectory generation, and risk-aware trajectory selection, and can be generalized to multi-UAV systems with a common latent representation.

3 System Model and Problem Formulation

In this section, we formally specify the environment and UAV dynamics that we propose, as well as the optimization goals of the proposed GWM. We use mathematical formulations to analyze UAV conditions, generate forecasts, streamline tillage, and assess risk-prone decisions.

We consider a dynamic traffic network represented as a directed graph, denoted by $\mathcal{G}_T$, comprising a set of nodes $\mathcal{V}$ and edges $\mathcal{E}$ that correspond to feasible UAV flight paths. The nodes include depots for UAV launch and landing, delivery points, and interchange points or candidate way points for dynamic routing, and the overall structure is formally expressed in Eq. (1):

$$\mathcal{G}_T = (\mathcal{V}, \mathcal{E}), \tag{1}$$

where $\mathcal{V} = \mathcal{V}_D \cup \mathcal{V}_P \cup \mathcal{V}_I$, with $\mathcal{V}_D$ denoting depots, $\mathcal{V}_P$ delivery locations, and $\mathcal{V}_I$ interchange points. Consider a fleet of N UAVs, $\mathcal{U} = \{1, 2, \ldots, N\}$, where each UAV $u \in \mathcal{U}$ is defined by a maximum energy capacity $E_{\max}$, maximum flight time $T_{\max}$, and a current state at time t. The UAV state is represented as a vector of its three-dimensional coordinates (x_u, y_u, z_u), instantaneous velocity $v_u(t)$, and remaining energy $E_u(t)$, as given in Eq. (2):

$$\mathbf{s}_u(t) = [x_u(t), y_u(t), z_u(t), v_u(t), E_u(t)]. \tag{2}$$

This abstract formulation of the environment and dynamics of UAVs provides the basis for trajectory planning, generation prediction, and risk-aware decision-making in the proposed GWM framework. We define a generative world model, $\mathcal{M}_G$, which predicts future environmental states over a horizon of H time steps. The model maps the current observed state $\mathcal{S}_t$ and feature embeddings $\mathcal{F}_t$, including weather, traffic flow, and UAV sensory data, to predicted future states $\hat{\mathcal{S}}_{t:t+H}$, as shown in Eq. (3):

$$\hat{\mathcal{S}}_{t:t+H} = \mathcal{M}_G(\mathcal{S}_t, \mathcal{F}_t), \tag{3}$$

such predictions depend on traffic density and obstacle positions, among other environmental factors. Diffusion models or transformer-based prediction networks can be used to implement the generative model, enabling UAVs to simulate various possible futures. For each future time step $t + h$ ($h = 1, \ldots, H$), the predicted state for each node $v \in \mathcal{V}$ is probabilistic and can be expressed inline as $\hat{\mathbf{s}}_v(t + h) \sim P_\theta(\mathbf{s}_v(t + h) \mid \mathcal{S}_t, \mathcal{F}_t)$, where P_θ is the learned generative distribution. This probabilistic predictive modeling allows UAVs to have an idea of several possible results, which develops the basis of resilient path planning and risk-aware decision-making.

Based on the generative predictions from Stage I, each UAV u generates a set of candidate trajectories, denoted as $\mathcal{T}_u = \{\tau_u^1, \tau_u^2, \ldots, \tau_u^K\}$, where each trajectory τ_u^k consists of a sequence of way points $[v_0, v_1, \ldots, v_H]$ with $v_h \in \mathcal{V}$ representing the h-th way point in the set of accessible nodes. The cost associated with each candidate trajectory, which accounts for energy consumption, flight time, and predicted risk from obstacles or traffic, is formally expressed in Eq. (4):

$$C(\tau_u^k) = \sum_{h=0}^{H} \left(\alpha_1 t_{v_h} + \alpha_2 e_{v_h} + \alpha_3 r_{v_h}\right), \tag{4}$$

where t_{v_h} denotes flight time, e_{v_h} represents energy consumption, and r_{v_h} is the predicted risk score, while α_1, α_2, and α_3 balance the relative importance of time, energy, and risk. The weighting coefficients α_1, α_2, and α_3 balance flight time, energy consumption, and predicted risk in the cost function. They are selected through validation-based tuning to achieve an effective trade-off between efficiency and safety. In general, a larger α_3 prioritizes safer trajectories, while higher α_1 and α_2 emphasize faster and more energy-efficient navigation, respectively. The objective of each UAV is to select the optimal trajectory, τ_u^*, that minimizes the expected cost under predicted environmental uncertainties. Formally, this is expressed in Eq. (5):

$$\tau_u^* = \arg\min_{\tau_u^k \in \mathcal{T}_u} \mathbb{E}\left[C(\tau_u^k)\right], \tag{5}$$

where $\mathcal{T}_u$ denotes the set of candidate trajectories generated in Stage II, and $C(\tau_u^k)$ is the trajectory cost composed of flight time, energy consumption, and risk. The optimization is constrained by maximum energy $E_{\max}$, maximum flight time $T_{\max}$, collision probability threshold ϵ, and waypoint accessibility within the traffic network. In multi-UAV scenarios, a shared latent space $\mathcal{Z} = f_\theta(\{\hat{\mathcal{S}}^u_{t:t+H}\}_{u=1}^N)$ is introduced to encode the predicted environmental states of all UAVs and support cooperative trajectory selection with reduced conflicts and improved collective efficiency. The joint optimization problem for all UAVs is expressed in Eq. (6):

$$\{\tau_1^*, \ldots, \tau_N^*\} = \arg\min_{\tau_u^k} \sum_{u=1}^{N} \mathbb{E}[C(\tau_u^k)] + \beta \cdot \text{Inter-UAV Conflict}(\tau_1, \ldots, \tau_N), \tag{6}$$

where β is a trade-off parameter balancing individual UAV risk and swarm-level coordination. This design guarantees that energy consumption, collision avoidance, and the synergistic use of generative cognition by a multi-UAV will enable adaptive swarm-level control.

The UAV navigation issue is described as risk-adaptive trajectory optimization in dynamical traffic conditions in the presence of uncertainty. The generative world model is used to predict future environmental states and determine the generation and selection of candidate trajectories, depending on energy and flight-time limitations and the risk of collision. Multi-UAV can also be associated with optional swarm-level coordination, which enhances efficiency, conflict avoidance, and general safety.

4 Proposed Methodology

The proposed risk-aware UAV navigation framework consists of three stages: GWM for predicting future environmental states, diffusion-based trajectory generation for producing candidate paths, and a Risk-Aware Decision Module for selecting the optimal trajectory based on energy consumption, collision risk, and mission objectives. As shown in Fig. 1, these stages are integrated to enable adaptive UAV navigation in dynamic and uncertain traffic environments.

Stage I: Generative World Modeling: In Stage I, each UAV constructs a generative model of the environment, enabling anticipation of multiple future scenarios. This stage allows UAVs to imagine the consequences of different navigation decisions prior to action. The inputs to the generative model include the current environmental state $\mathcal{S}_t$, UAV sensory data $\mathcal{F}_t$, and information about traffic patterns, dynamic obstacles, and weather conditions. Based on these inputs, the output of this stage is the predicted environmental states over a horizon H, denoted as $\hat{\mathcal{S}}_{t:t+H}$. The generative model follows the probabilistic future-state formulation already defined in Eq. (3). Instead of restating the equation, this stage operationalizes it through a Transformer-based sequence prediction model or a diffusion-based world model. The model encodes the current UAV state, sensory features, traffic density, obstacle locations, and weather-related contextual variables into a latent representation, and then predicts a distribution of plausible future environmental states across the prediction horizon H. It is trained in supervised mode on trajectory data using mean squared error for continuous variables and cross-entropy or regularization loss for probabilistic state representations. Hyperparameters, including learning rate, batch size, latent dimension, and prediction horizon, are selected through validation-based tuning. The output of this stage is passed to Stage II as a distribution of predicted traffic, obstacle, and environmental states, enabling anticipatory UAV planning rather than purely reactive navigation. The novelty of this stage lies in enabling UAVs to plan trajectories based on imagined future scenarios, rather than relying solely on reactive navigation. To enhance reproducibility, the generative world model is applied as a transformer-based sequence prediction framework that jointly transforms UAV state variables, including position, velocity, and energy, with environmental variables, such as traffic density and obstacle locations, and context conditions into a latent representation. The model estimates probabilistic future environmental states across a set horizon, is trained in a supervised mode on trajectory data, and uses mean squared error for continuous states or cross-entropy or irregularity loss for probabilistic representations of states. Critical hyperparameters such as learning rate, batch size, latent dimension, and prediction horizon are selected via validation-based hyperparameter tuning.

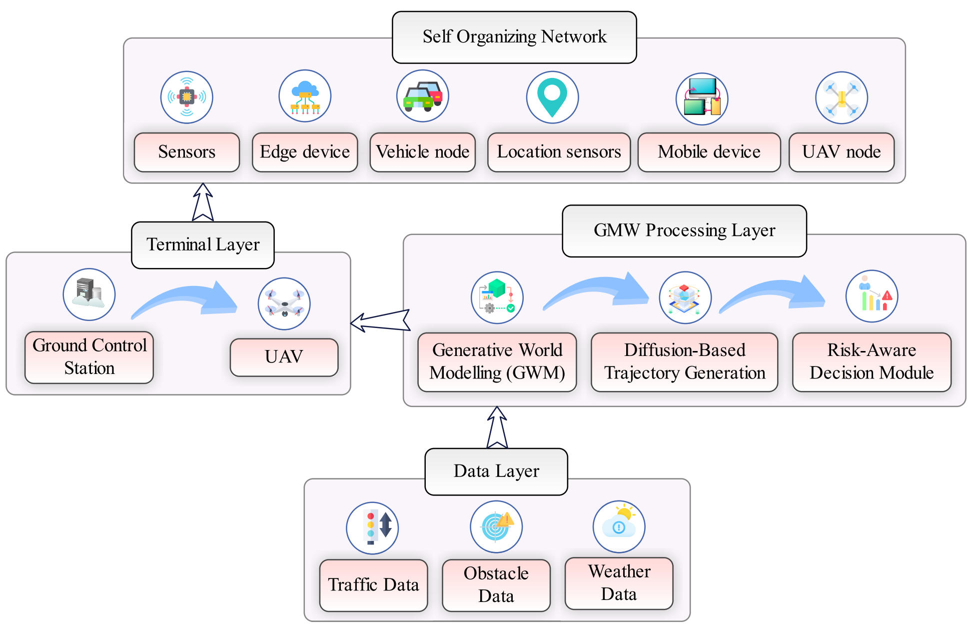

Figure 1: Architecture of the proposed Generative World Modeling (GWM) framework for risk-aware UAV navigation.

Stage II: Diffusion-Based Trajectory Generation: In Stage II, each UAV generates multiple candidate trajectories from the predicted environment states in Stage I using diffusion-based generative models. Each UAV generates the candidate trajectory set $\mathcal{T}_u = \{\tau_u^1, \ldots, \tau_u^K\}$, where each candidate trajectory consists of a sequence of feasible waypoints across the traffic network. For consistency with the system formulation, each candidate is evaluated using the trajectory-cost function already defined in Eq. (4), which jointly considers flight time, energy consumption, and predicted risk.

To remain consistent with the discrete graph model, the diffusion process is performed in a continuous latent space constructed from traffic-network node embeddings. The forward process perturbs these embeddings with Gaussian noise, while the reverse process reconstructs feasible trajectory representations. The generated latent trajectories are then projected back to the discrete traffic graph by selecting valid nodes and connectivity-preserving edges. Infeasible trajectories that violate energy, flight-time, or collision-probability constraints are discarded, and only feasible candidates are passed to the Stage III risk-aware decision module. This procedure increases trajectory diversity while preserving the topological structure of the UAV traffic network. These embeddings are perturbed by the forward process using Gaussian noise and restored to their original form through the reverse process to produce representations of the trajectories. These continuous trajectories are then broken down into discrete ones by projecting back onto the discrete graph, selecting their feasible nodes and valid edges based on connectivity constraints. The formulation allows a variety of trajectory generations without affecting the topological structure of the UAV traffic network. The generative model is used to sample latent variables and then decode them based on the predicted environmental states to give candidate trajectories. Violent trajectories are rejected, and those that comply with the energy, flight time, or collision constraint are forwarded to the Stage III risk-aware parameter selection. This procedure enhances stability in changing, unpredictable urban traffic conditions.

Stage III: Risk-Aware Decision Module: In Stage III, the risk-aware decision module examines the set of candidate trajectories produced by Stage II and selects the best trajectory to guide UAV navigation, thereby reducing anticipated expenses under uncertainties. The risk-aware decision module selects the optimal trajectory using the objective already defined in Eq. (5). For each candidate path, the module estimates expected cost under predicted uncertainty and computes cumulative collision risk from the world-model forecasts. The risk score represents the probability of collision with dynamic obstacles or neighboring UAVs within the modeled safety radius across the prediction horizon. Candidates exceeding the collision threshold ε the maximum energy budget Emax, or the maximum flight-time limit Tmax are eliminated. Among the remaining candidates, the trajectory with the lowest expected cost is selected and executed in a receding-horizon manner, with predictions updated continuously at each time step. These probabilities are summed throughout the prediction horizon to receive the cumulative trajectory risk. A collision threshold ε is provided as the maximum permissible probability of collision, and any trajectory whose probability exceeds the threshold is eliminated. This formulation incorporates predictive uncertainty into safe trajectory selection.

The decision-making process steps include computation of the predicted cost of every candidate trajectory in the case of environmental uncertainty, calculation of the risk of normal trajectories by predicted obstacle positions, traffic dynamics and UAV-to-UAV collisions in the case of multiple agents, choosing the trajectory τ_u^* with the lowest expected cost and acceptable risk, and implementing it through a sequence of predictions updated throughout the Stage I. The framework also ensures that UAVs operate safely, efficiently, and adaptively in dynamic and uncertain environments.

Multi-UAV and Swarm Extension: For scenarios involving multiple UAVs operating simultaneously, a shared latent space, $\mathcal{Z}$, is defined to facilitate cooperative decision-making. This latent space is obtained by mapping the generative predictions of all N UAVs through a function f_θ, which encodes each UAV's predicted environmental states into a shared representation, expressed inline as $\mathcal{Z} = f_\theta(\{\hat{\mathcal{S}}^u_{t:t+H}\}_{u=1}^N)$. For multi-UAV scenarios, the swarm extension uses the shared-latent-space formulation introduced in Eq. (6). The latent representation aggregates predicted environmental states from all UAVs through a common encoder, allowing cooperative selection of trajectories while reducing inter-UAV conflicts. Depending on deployment requirements, the shared latent representation may be implemented in centralized or decentralized form, with compact low-dimensional embeddings exchanged at fixed intervals to reduce communication overhead and control latency. This enables coordinated, low-conflict, and energy-efficient navigation in swarm operations without restating the full optimization equation. The combined latent space $\mathcal{Z}$ combines the predicted environmental states of all UAVs using a common encoder, which delivers a uniform global traffic representation. It may be used in a decentralized or centralized setting, where low-dimensional latent embeddings are transferred at discrete, fixed points to achieve bandwidth savings and control latency. This extension enables coordinated, low-conflict, and energy-efficient navigation in multi-UAV swarm scenarios.

The suggested methodology comprises three primary stages: GWM to predict environmental dynamics, diffusion-based trajectory generation to produce viable candidate paths, and a Risk-Aware Decision Module to select the most appropriate trajectory based on energy, flight time, and safety constraints. In the case of multi-UAV, voluntary swarm coordination enables the UAVs to exchange generative forecasts to enhance collective navigation. Collectively, the components facilitate the safe, efficient, and adaptive navigation of the UAV in the changing traffic conditions as summarized in Algorithm 1.

Algorithm 1: Generative world modeling for risk-aware UAV navigation

Input: UAV state $\mathbf{s}_u(t)$, environment $\mathcal{S}_t$, features $\mathcal{F}_t$, constraints $E_{\max}$, $T_{\max}$, horizon H, UAVs N (optional)
Output: Optimal trajectory τ_u^*; swarm-coordinated trajectories if $N > 1$

```
Initialize: Set s_u(t), E_u = E_max, T_u = 0, construct graph G_T
Generative World Modeling:
for each UAV u do
    Encode S_t, F_t into latent space
    Predict Ŝ_{t:t+H} = M_G(S_t, F_t)
end for
Diffusion-Based Trajectory Generation:
for each UAV u do
    Generate candidate trajectories T_u = {τ_u^1, ..., τ_u^K}
    Compute C(τ_u^k) = Σ_{h=0}^{H} (α_1 t_{v_h} + α_2 e_{v_h} + α_3 r_{v_h})
Filter trajectories violating E_max, T_max, Pr(collision) ≤ ϵ
end for
Risk-Aware Decision:
for each UAV u do
    Select τ_u^* = arg min_{τ_u^k ∈ T_u} E[C(τ_u^k)]
end for
Swarm Coordination (Optional, N > 1):
Construct shared latent space Z and optimize total cost including inter-UAV conflicts
Continuous Update: Update s_u(t + 1); repeat predictions and selections
return τ_u^* and swarm-coordinated trajectories if applicable
```

5 Simulation and Experimental Setup

The GWM framework became the subject of the proposed research and the level of its performance was tested on publicly available UAV trajectory and traffic datasets. Using Python, the simulations were conducted in Google Colab under controlled conditions to study UAV navigation characteristics under low and high traffic conditions, dynamic obstacles, and single- and multi-UAV (swarm) environments, with sufficient reproducibility and scalability.

To simulate real-world UAV navigation scenarios, we used the SWIFTraj repository, which provides trajectories of vehicles in urban and freeway environments observed by UAVs. The dataset comprises long trajectories of moving vehicles, providing realistic mobility patterns of obstacles and traffic that can be used to assess trajectory planning, collision avoidance, and energy expenditure in UAV operation. To be fair and reproducible, the SWIFTraj dataset is aligned with UAV navigation by treating the 2D trajectories as time-dependent multi-agent traffic patterns and adding an altitude axis, providing a simplified view of the 3D space. The resultant state-of-the-art trajectories are normalized and overlaid over the UAV traffic network, and collision modeling constraints are added to the state space through vertical separation constraints. Then, using an 80/20 split, the dataset is divided into training and test sets. Every method is tested at the same UAV conditions, environmental conditions, and working conditions, and the experiment is replicated in several runs with averaged outcomes reported to allow similar comparisons. The simulation environment follows the directed traffic-graph formulation introduced in Eq. (1). For the experimental instantiation, the graph contains depots $\mathcal{V}_D = \{D_1, D_2, \ldots, D_5\}$, delivery points $\mathcal{V}_P = \{P_1, \ldots, P_{25}\}$, and interchange points $\mathcal{V}_I = \{I_1, \ldots, I_{30}\}$, which serve as waypoints for dynamic routing. The directed edges E represent feasible UAV flight paths constrained by UAV energy capacity, collision radius, and obstacle positions derived from the SWIFTraj dataset. The dynamic obstacles were obtained directly from vehicle trajectories in the dataset to provide realistic motion patterns for UAV path planning and collision-avoidance evaluation. Traffic density scenarios were defined as low ($\alpha = 0.2$), medium ($\alpha = 0.6$), and high ($\alpha = 1.0$), as shown in Eq. (7):

$$\alpha = \begin{cases} 0.2 & \text{low traffic,} \\ 0.6 & \text{medium traffic,} \\ 1.0 & \text{high traffic,} \end{cases} \tag{7}$$

where the dynamic obstacles were directly derived on vehicle paths in the database to offer realistic movement pattern in UAV path planning and collision avoidance.

The simulated UAVs were configured with realistic operational characteristics, including a maximum flight time of $T_{\max} = 25$ min, a maximum energy capacity of $E_{\max} = 100$ units, an average flight speed of $v_{\text{avg}} = 15$ m/s, and a collision radius of $r_{\text{UAV}} = 2$ m. The environmental effects, including obstacle density and differences in vehicle velocity, as reported in the SWIFTraj dataset, were also simulated. They were used to assess the feasibility of UAV paths, energy usage, and collision likelihoods, thereby ensuring that simulated conditions are highly realistic for operations.

The simulations were conducted in Python 3.10 on Google Colab using NumPy, Pandas, NetworkX, Matplotlib, Seaborn, and SciPy. The runtime environment included an Intel Xeon 2.3 GHz CPU, 12 GB RAM, and an NVIDIA Tesla T4 GPU, providing efficient support for large-scale UAV trajectory simulation and reproducible evaluation. To evaluate the proposed GWM framework, we compared it with seven baseline methods: A*, Dijkstra, Rapidly-exploring Random Tree (RRT), RL, Conflict-based search (CBS), Hybrid RL+CBS, and Predictive RL. These baselines represent classical, learning-based, and multi-agent planning approaches, providing a comprehensive basis for assessing the efficiency and robustness of the proposed method.

UAV navigation performance was evaluated using mission success rate, average delivery time, energy consumption, collision rate, safety score, path optimality, and swarm coordination. Simulations were conducted under realistic conditions with low ($\alpha = 0.2$), medium ($\alpha = 0.6$), and high ($\alpha = 1.0$) traffic densities derived from the SWIFTraj dataset, with dynamic obstacles introduced from vehicle trajectories. Both single-UAV and multi-UAV swarm scenarios were considered, with swarm experiments involving 5–10 UAVs sharing latent-space predictions, alongside stress tests under temporary obstructions, changing obstacle density, and varying wind conditions.

The experimental environment is a composition of the SWIFTraj dataset, Python Colab implementation, and realistic UAV operating parameters, in order to test the proposed GWM framework in the context of various traffic densities, dynamic obstacles, single- and multi-UAV rules, and circumstances with seven established baseline approaches. To be fair and reproducible, each baseline is evaluated under the same set of conditions, with hyperparameters chosen either from the literature or selected via validation. The results are reported as mean and standard deviation, with multiple runs and test statistics, and the ablation analysis is provided accordingly to enhance the validity of the assessment.

6 Results and Discussion

The proposed GWM framework was evaluated under varying traffic loads, moving obstacles, and single- and multi-UAV swarm scenarios, and compared with seven baseline methods: A*, Dijkstra, RRT, Reinforcement Learning, Conflict-Based Search, Hybrid RL+CBS, and Predictive RL. Performance was assessed using mission success rate, average delivery time, energy consumption, collision rate, safety score, path optimality, and swarm coordination. The greatest performance of the proposed framework is conducted by its integration of predictive modeling, generative trajectory sampling, and risk-aware decision-making, which together enable better adaptation to dynamic environments and a more effective balance between safety and efficiency.

6.1 Mission Success Rate

The mission success rate represents the percentage of UAV missions completed without failure and was evaluated under varying traffic densities. Under low traffic conditions ($\alpha = 0.2$), the proposed GWM framework achieved a mission success rate of 98.5%, compared to 92.1% for RL and 88.7% for CBS. For medium traffic ($\alpha = 0.6$), GWM maintained a success rate of 95.3%, outperforming Predictive RL at 87.6% and Hybrid RL + CBS at 83.2%. Under high traffic conditions ($\alpha = 1.0$), GWM achieved 91.7%, whereas A* and RRT methods dropped below 76%. These findings show that a generative world-modeling approach is a meaningful way to enhance the reliability of a given mission by predicting traffic and changing impediments. The detected quantitative data are summarized in Table 1 and the comparative tendencies are shown in Fig. 2.

Table 1: Mission success rate (%) of UAVs under different traffic densities. GWM significantly outperforms all baselines.

Traffic Density	A* (%)	Dijkstra (%)	RRT (%)	RL (%)	CBS (%)	Hybrid RL+CBS (%)	Predictive RL (%)	GWM (Proposed) (%)
Low ($\alpha = 0.2$)	85.2	83.5	80.1	92.1	88.7	90.5	91.3	98.5
Medium ($\alpha = 0.6$)	78.4	76.2	73.5	84.2	81.0	83.2	87.6	95.3
High ($\alpha = 1.0$)	75.4	73.1	70.5	78.9	75.6	83.2	80.4	91.7

6.2 Average Delivery Time

The delivery time parameter was the time difference between the UAV's departure and the package's delivery, and its comparison was performed in single-UAV and multi-UAV swarm modes. The GWM framework presented in single-UAV operations has also saved 14%–18% time in delivery compared to their counterparts that employ RL. Co-ordinated trajectories that share latent-space predictions for a swarm of multi-UAVs also reduced the delivery time by 22% compared to CBS. GWM trajectory generation uses a diffusion approach that enables UAVs to select routes with lower energy expenditure that evade evolving impediments. The correspondingly summarized Table 2 of the results is presented in Fig. 3.

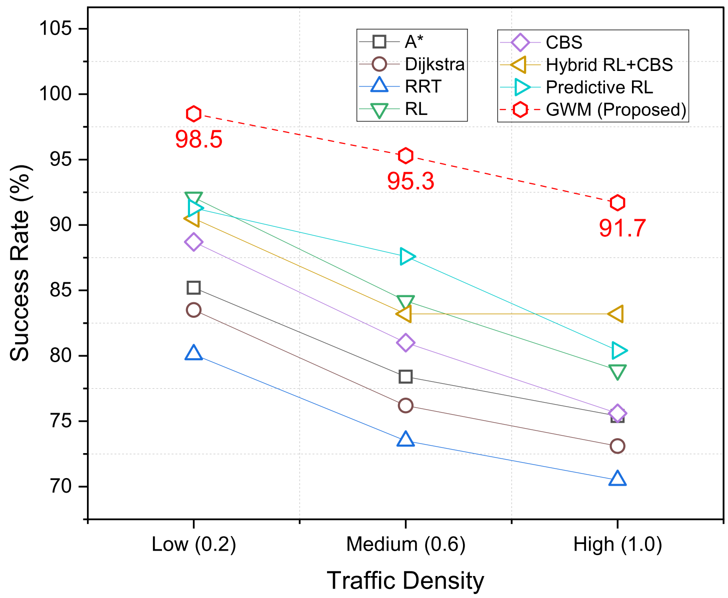

Figure 2: UAV mission success rate at different traffic densities.

Table 2: Average delivery time (minutes) for single and multi-UAV missions. GWM reduces delivery time by up to 22% for swarm operations.

Traffic Density	Single UAV A*	Single UAV RL	Single UAV CBS	Multi-UAV CBS	Multi-UAV GWM	Single UAV GWM
Low (α = 0.2)	18.4	17.2	19.1	17.8	13.8	15.7
Medium (α = 0.6)	22.5	21.3	23.1	22.0	17.1	18.4
High (α = 1.0)	28.1	26.7	27.9	26.5	20.7	21.5

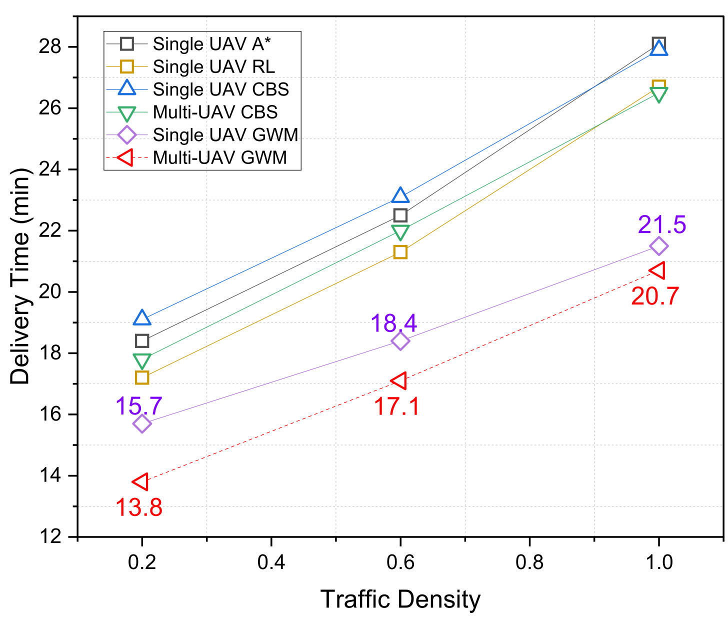

Figure 3: Average delivery time at different traffic densities.

6.3 Energy Consumption

One of the primary measures of UAV endurance is energy efficiency, which was evaluated under varying traffic and operating conditions. The GWM framework shown for single-UAV missions entailed 21.3 units per mission under medium traffic density, and 27.5 and 31.2 units under Predictive RL and A*, respectively. In swarm operations, cooperative latent-space planning refined the number of units of energy per individual UAV to be 19.8 units, which illustrates the benefit of multi-UAV coordinated operations. The corresponding quantitative results are summarized in Table 3 and depicted in Fig. 4.

Table 3: Energy consumption (units) per UAV mission. GWM demonstrates improved energy efficiency for both single and multi-UAV operations.

Traffic Density	A*	RL	CBS	Predictive RL	GWM (Single UAV)	GWM (Swarm UAV)
Low (α = 0.2)	28.5	25.7	27.2	24.8	20.1	18.9
Medium (α = 0.6)	31.2	28.9	30.1	27.5	21.3	19.8
High (α = 1.0)	35.0	32.8	33.5	31.2	23.5	21.9

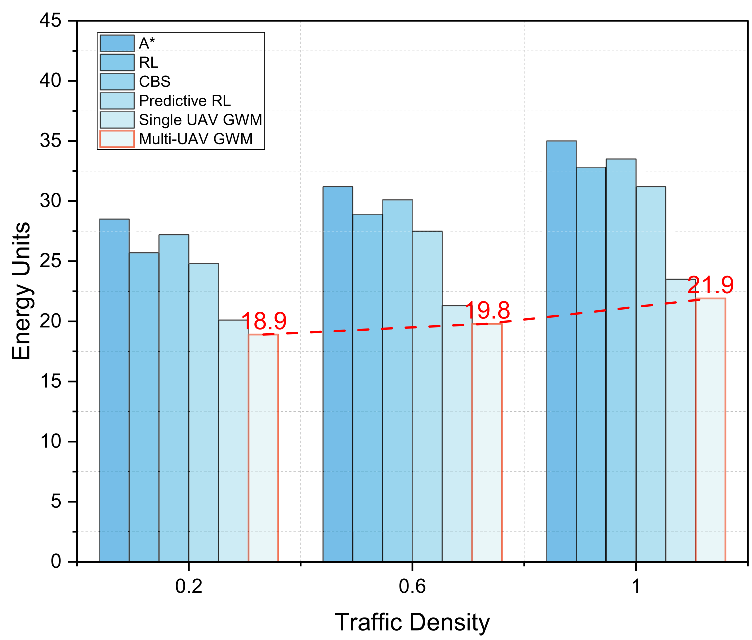

Figure 4: Energy consumption per UAV at different traffic densities.

6.4 Collision Rate and Safety

One of the most pressing issues in UAV navigation is collision avoidance, particularly when UAVs are concentrated within a traffic network. The suggested GWM framework in single UAV missions hit 0.9% of the suggested collision rate, which is significantly lower than the A* framework at 5.4% and the RL framework at 3.7%. In the swarm operations of 5–10 UAVs, the collision probability increased slightly to 1.8%; however, with a shared generative latent-space, an investigation showed that inter-UAV conflicts decreased by 32% relative to CBS, as demonstrated in Fig. 5. The safety score, a composite index of energy efficiency and collision avoidance, was 94.6% for single-UAV missions and 92.1% for swarm operations. These findings underscore the utility of the GWM framework for enhancing the efficiency and safety of UAV navigation. Table 4 presents the related quantitative data, and Fig. 6 shows their illustration.

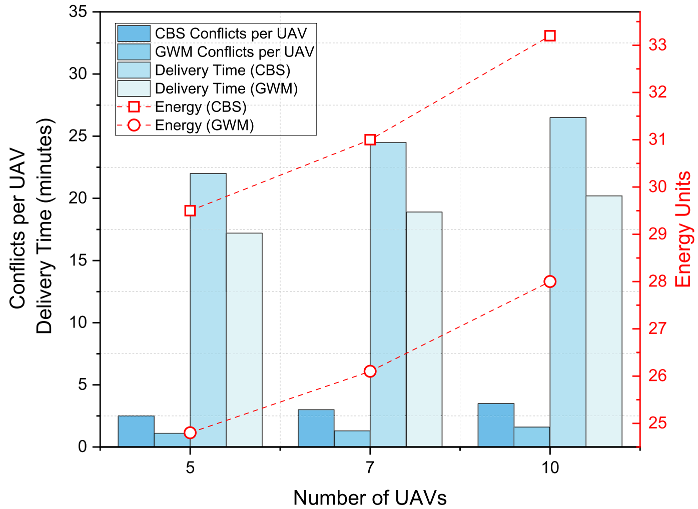

Figure 5: Swarm coordination showing conflicts, delivery time, and energy.

Table 4: Collision rate (%) and safety score (%) for single and multi-UAV missions. GWM reduces collision risk while maximizing safety.

Metric	Single UAV A*	Single UAV RL	Single UAV CBS	Multi-UAV CBS	GWM (Single UAV)	GWM (Swarm UAV)
Collision Rate (%)	5.4	3.7	2.8	3.2	0.9	1.8
Safety Score (%)	81.2	86.5	88.3	85.7	94.6	92.1

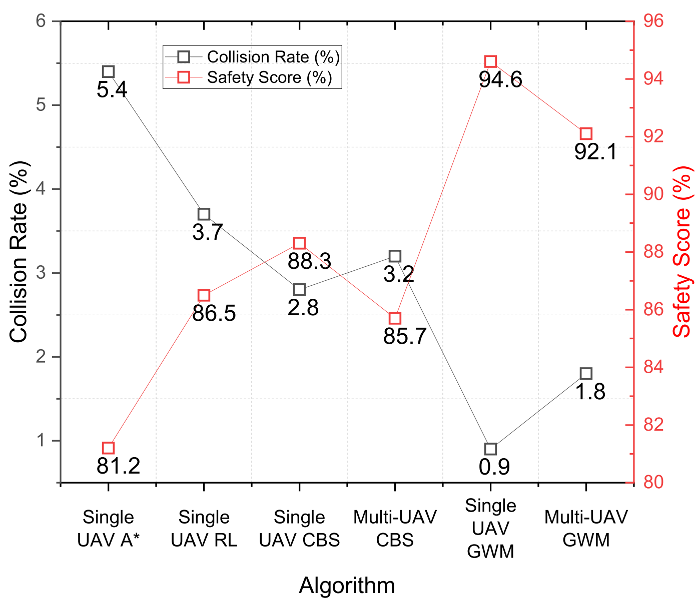

Figure 6: Comparison of collision rate and safety score.

6.5 Path Optimality

Path optimality measures the efficiency of UAV paths relative to theoretically optimal paths, such as those with minimum cost. The proposed GWM achieved high optimality of 87.2%, 84.5%, and 81.3% under low, medium, and high traffic, respectively. Compared with other baseline approaches, including RRT with 72%–75% and Predictive RL with 78%–80% optimality, GWM achieves a better balance among path optimality, trajectory safety, and energy efficiency. The results are represented in Fig. 7.

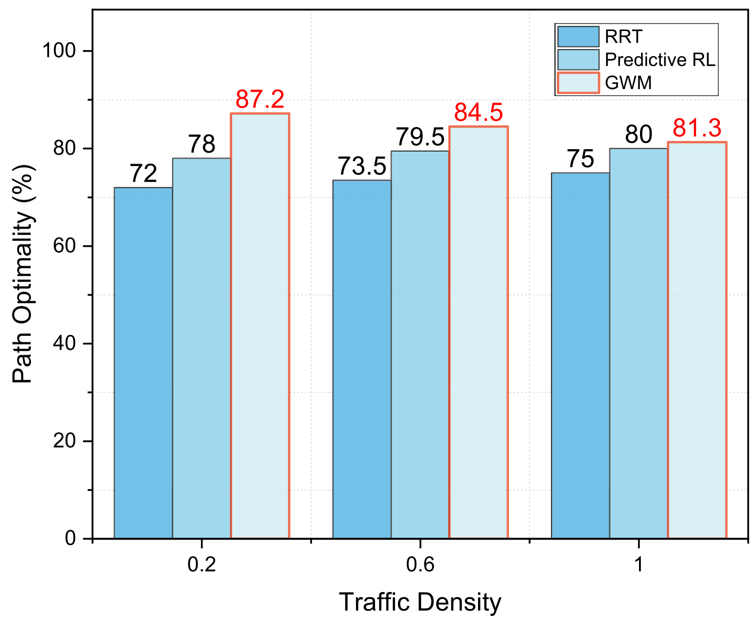

Figure 7: Path optimality at different traffic densities.

In order to understand the contribution of an individual component further, an ablation study is done by removing important modules in the proposed framework. Table 5 demonstrates that without the generative world model, performance is considerably lower because of the absence of predictive power, and that not using the diffusion-based trajectory generation restricts the variety of possible paths. Similarly, eliminating the risk-aware decision module will result in unsafe or suboptimal path stops. The complete model is most successful and demonstrates the efficacy of combining predictive modeling, generative path generation, and risk-sensitive optimization into a single structure.

Table 5: Ablation study evaluating the contribution of each component of the proposed framework.

Model Variant	Mission Success Rate (%)	Energy Consumption (Wh)	Collision Rate (%)	Path Optimality (%)
Full Model (GWM + Diffusion + Risk)	92.3 ± 1.2	118.6 ± 3.4	3.1 ± 0.8	89.7 ± 1.5
Without Generative World Model	78.5 ± 2.1	134.2 ± 4.6	9.8 ± 1.4	76.3 ± 2.0
Without Diffusion Module	81.2 ± 1.8	129.7 ± 3.9	7.4 ± 1.1	79.5 ± 1.7
Without Risk-Aware Module	75.6 ± 2.4	121.4 ± 3.1	13.2 ± 1.9	74.8 ± 2.3

Experimental findings allow us to draw several main conclusions about the efficiency of the GWM framework. First, generative imagination promotes navigation by enabling UAVs to plan routes in advance, thereby reducing mission failures and collisions. Second, a diffusion-generated trajectory is less susceptible to uncertainty, offering many candidate paths that UAVs can select to achieve safety and energy efficiency. Third, the risk-aware decision module enhances overall safety by accounting for energy limitations, collision risk, and forecasted traffic when selecting optimal routes. Fourth, multi-UAV shared latent-space planning with swarm-level generative cognition mitigates inter-UAV conflicts, minimizes energy usage, and reduces delivery time. Lastly, the GWM framework performs strongly on the metrics, consistently outperforming classical, RL-based, and conflict-based baseline approaches, indicating its effectiveness in dynamic and uncertain traffic networks.

7 Conclusion

In this paper, a GWM architecture of risk-aware autonomous UAV navigation in changing traffic networks was suggested. By combining generative AI, diffusion-based trajectory generation, and risk-based decision compression, UAVs can anticipate traffic and obstacle dynamics, traverse energy-efficient, systematically safe paths, and respond in real time to environmental vagaries. The overall outcomes of the simulation show that GWM is effective across major parameters, including mission success rate, average delivery time, energy consumption, collision avoidance, and angular efficiency of the paths, thereby meeting the needs of high-performance and adaptive UAV missions.

The suggested system integrates predictive actions for changing traffic and environmental states, trajectory generation using diffusion models, and risk-aware actions within a single architecture, and optionally joint coordination in the latent space when using many UAVs. The experimental analysis at varying traffic conditions has shown that it can enhance safety, efficiency, and mission performance. Nevertheless, the approach can entail computational cost and be vulnerable to prediction error, communication delays, and physical constraints on hardware implementation. Future developments will thus aim at any physical UAV platform or use of UAVs in integration with UAV traffic management systems, and additionally optimizing it for scalable, real-time, and safety-critical uses.

Acknowledgement: Not applicable.

Funding Statement: Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2026R435), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Author Contributions: Conceptualization, Alaa M. Momani and Deema Mohammed Alsekait; methodology, Mahmoud Ahmad Al-Khasawneh; software, Siti Hajar Othman; validation, Nikunj Sharma; formal analysis, Wee How Khoh; investigation, Wee How Khoh; resources, Nikunj Sharma; data curation, Ibraheem Al-Tarawneh; writing—original draft preparation, Alaa M. Momani; writing—review and editing, Deema Mohammed Alsekait and Mahmoud Ahmad Al-Khasawneh; visualization, Nikunj Sharma and Siti Hajar Othman; supervision, Wee How Khoh; project administration, Mahmoud Ahmad Al-Khasawneh; funding acquisition, Deema Mohammed Alsekait. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: Data will be available on suitable request from the authors.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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