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Generative AI in Transportation Planning: Emerging Applications, Opportunities and Challenges

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ABSTRACT

Transportation planning is becoming more complex due to rapid urbanization, increase in vehicle ownership, climate concerns and dynamic travel behaviour of people. Traditional modelling and simulation approaches often require large manual effort and sometimes fails to represent real-world uncertainty. Recently, Generative Artificial Intelligence (Generative AI) has shown significant potential to transform how transportation systems are analysed, designed and optimized. Generative AI models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Large Language Models (LLMs) and diffusion models can generate realistic traffic patterns, synthetic mobility data, road network designs and even support decision making in policy formulation. This paper presents a comprehensive review on the role of Generative AI in transportation planning. The study discusses various techniques, applications in traffic prediction, demand modelling, infrastructure planning, autonomous mobility, and smart city integration. Benefits, limitations and future research directions are also highlighted. The review indicates that Generative AI can significantly improve data-driven transportation planning while reducing cost and time, however issues related to data quality, interpretability and ethics needs further attention.

KEYWORDS: *Generative AI, Transportation Planning, Traffic Modelling, GAN, Smart Mobility, Urban Transport, Synthetic Data*

INTRODUCTION

Transportation planning is a critical component of urban and regional development. It involves forecasting travel demand, designing transport infrastructure, managing traffic operations and improving mobility for people and goods. Traditionally, planners relied on statistical models, surveys, simulation tools and historical traffic data. But with rapid changes in mobility patterns and availability of large scale data from sensors, GPS, mobile phones, the need for intelligent data-driven approaches has increased.

Artificial Intelligence (AI) already has applications in traffic management and prediction. But generative AI is a relatively new branch which can create new data instances that resemble real world data. Instead of only predicting outcomes, generative models can simulate scenarios, produce synthetic traffic flows, design network layouts and help planners to visualize future conditions.

Generative AI models are capable of learning hidden patterns from transportation datasets and produce realistic outputs. This is useful where real data is limited, sensitive, or expensive to collect. Hence, Generative AI has started to gain attention in transportation planning research.

This paper reviews how generative AI techniques are applied in various aspects of transportation planning and discusses its future scope.

OVERVIEW OF GENERATIVE AI TECHNIQUES

Generative Artificial Intelligence (GenAI) encompasses a class of machine learning models capable of learning the underlying distribution of data and producing new, realistic samples that resemble the original training data. Unlike discriminative models that focus on classification or prediction, generative models **create** data—such as images, text, time-series signals, simulations, and scenarios.

In transportation and mobility research, generative AI is increasingly used for:

- Synthetic traffic and mobility data generation
- Scenario simulation for planning and safety analysis
- Travel demand and behavior modeling
- Infrastructure monitoring and visualization

- Policy analysis and automated reporting

The major generative AI techniques relevant to transportation systems are described below.

Generative Adversarial Networks (GANs)

Generative Adversarial Networks, introduced by Goodfellow et al., consist of two neural networks trained simultaneously:

- **Generator** – produces synthetic data samples
- **Discriminator** – distinguishes between real and fake samples

The two networks compete in a minimax game, forcing the generator to produce increasingly realistic outputs.

Working Principle

The generator takes random noise as input and attempts to create data resembling real traffic or mobility patterns. The discriminator evaluates whether the data is real or generated. Over iterations, the generator learns the true data distribution.

Applications in Transportation

GANs are widely used for generating realistic spatial, visual, and temporal transportation data:

- Synthetic **traffic flow datasets** when real data is limited or privacy-restricted
- Generation of **road scene images** for training autonomous vehicle vision systems
- Simulation of **vehicle trajectories and movement patterns**
- Enhancement of **low-resolution CCTV traffic images**
- Data augmentation for **accident detection and congestion prediction models**

GAN variants such as CycleGAN, StyleGAN, and Conditional GAN (cGAN) enable scenario-specific data generation, such as night-time traffic scenes, rainy conditions, or high-density congestion patterns.

Variational Autoencoders (VAEs)

Variational Autoencoders are probabilistic generative models that learn latent representations of data. Unlike GANs, VAEs model the data distribution explicitly using probability theory.

Working Principle

VAEs consist of:

- **Encoder** – compresses input data into a latent probability distribution
- **Decoder** – reconstructs data samples from the latent space

By sampling from this latent space, VAEs can generate new data that follow learned mobility or traffic patterns.

Applications in Transportation

VAEs are particularly effective for modeling stochastic and uncertain behavior:

- **Mobility demand prediction** under uncertainty
- Modeling **travel behavior patterns** of commuters
- Generation of **origin–destination (OD) matrices**
- Simulation of **public transport usage patterns**
- Probabilistic modeling of **route choice behavior**

Because VAEs capture variability and uncertainty, they are well suited for travel demand forecasting where randomness and human behavior play key roles.

Diffusion Models

Diffusion models are a recent breakthrough in generative AI. They work by gradually adding noise to data and then learning to reverse this process to reconstruct meaningful samples.

Working Principle

- **Forward process:** Data is progressively corrupted with noise.
- **Reverse process:** A neural network learns to denoise and recover structured data.

This iterative refinement allows diffusion models to generate highly detailed and stable outputs.

Applications in Transportation

Diffusion models are gaining attention for:

- **Traffic state simulation** across large urban networks
- Generation of **multi-modal transportation scenarios** (vehicles, pedestrians, cyclists)

- Simulation of **extreme events** such as accidents or bottlenecks
- High-fidelity **urban mobility simulations** for smart city planning
- Synthetic **time-series traffic flow data** with temporal consistency

Compared to GANs, diffusion models offer more stable training and better diversity in generated samples, making them ideal for complex traffic simulations.

Large Language Models (LLMs)

Large Language Models, such as GPT-based systems, are generative models trained on vast text corpora. They generate coherent text, summarize documents, answer questions, and assist in reasoning tasks.

Working Principle

LLMs learn linguistic patterns and contextual relationships between words and sentences, enabling them to produce human-like textual outputs.

Applications in Transportation and Planning

LLMs support knowledge-driven tasks rather than numeric data generation:

- Automated **traffic incident report generation** from sensor logs
- Interpretation of **transportation planning documents** and regulations
- Assisting policymakers with **scenario analysis and decision support**
- Generating **technical reports**, feasibility studies, and summaries
- Extracting insights from **public feedback and survey data**
- Conversational interfaces for **smart mobility management systems**

When integrated with traffic databases and simulation tools, LLMs can serve as intelligent assistants for planners and traffic engineers.

APPLICATIONS OF GENERATIVE AI IN TRANSPORTATION PLANNING

Generative AI is transforming transportation planning by enabling planners to **simulate, augment, and analyze** mobility systems even when real-world data is scarce, expensive, privacy-sensitive, or incomplete. By learning patterns from existing datasets, generative models can create realistic synthetic data, plausible future scenarios, and decision-support artifacts that enhance planning accuracy and resilience.

Synthetic Traffic Data Generation

Collecting real traffic data through sensors, cameras, GPS traces, and surveys is costly, time-consuming, and often restricted by privacy regulations. Moreover, many cities—especially in developing regions—lack dense sensing infrastructure, resulting in incomplete datasets. Generative AI, particularly **Generative Adversarial Networks (GANs)** and **Diffusion Models**, offers a powerful solution by producing **synthetic traffic datasets** that preserve the statistical and spatio-temporal characteristics of real traffic without exposing sensitive information.

How It Works

Generative models are trained on available traffic datasets such as:

- Traffic flow counts from loop detectors
- GPS trajectories from vehicles
- CCTV traffic images
- Speed and density time-series data
- Origin–Destination (OD) matrices

After learning the underlying data distribution, the model can generate new samples that mimic:

- Hourly/daily/seasonal traffic patterns
- Peak-hour congestion behavior
- Road-type-specific flow characteristics (arterial, highway, intersection)
- Vehicle movement trajectories across networks

Key Benefits

1. **Privacy Preservation**

Synthetic datasets do not contain identifiable vehicle or traveler information, addressing legal and ethical concerns.

2. **Cost Reduction**

Reduces dependence on large-scale sensor deployment and repeated field surveys.

3. **Data Augmentation**

Enhances small or imbalanced datasets for training traffic prediction and incident detection models.

4. **Rare Event Simulation**

Enables creation of uncommon scenarios such as severe congestion, accidents, road closures, or festival traffic surges that are difficult to capture in real life.

5. **Scalability for New Cities**

Traffic patterns from data-rich cities can be used to generate realistic datasets for data-poor regions through transfer learning and GAN-based synthesis.

Table: 1

Application	Generative Model Used	Purpose
Traffic flow data	GAN	Generate realistic traffic counts
OD Matrix	VAE	Travel demand estimation
GPS traces	GAN	Vehicle trajectory simulation

Travel Demand Modelling

Travel demand modelling aims to estimate how many trips will occur, where they will originate and terminate, which modes will be used, and at what times. Traditional four-step models and activity-based models rely heavily on historical surveys and census data, which often fail to capture rapid socio-economic changes, emerging mobility services, or behavioral uncertainty.

Generative models such as **VAEs, GANs, and diffusion models** can learn latent patterns from historical travel surveys, smart card data, mobile GPS traces, and land-use information to **simulate realistic travel demand under varying socio-economic scenarios**.

Capabilities

- Generation of **synthetic Origin–Destination (OD) matrices** for future years

Simulation of travel behavior under:

- Population growth
- Income changes
- Fuel price variations
- Work-from-home policies
- Introduction of metro/BRT systems

- Modeling **mode shift behavior** (e.g., private car to public transport)
- Capturing uncertainty and randomness in commuter decisions

Planning Benefits

- Test policy scenarios before real implementation
- Evaluate impact of new transit corridors on travel demand
- Forecast ridership for proposed public transport systems
- Analyze equity impacts across socio-economic groups

Road Network Design and Optimization

Designing efficient road networks involves balancing land use, environmental constraints, construction cost, and projected traffic load. Generative AI can automatically produce **multiple feasible design alternatives** by learning from existing urban layouts and traffic patterns.

Using GANs and evolutionary generative approaches, planners can input constraints such as:

- Land-use maps
- Population density distribution
- Terrain and environmental restrictions
- Expected traffic demand

The model then proposes optimized road alignments and network topologies.

Applications

- Generation of alternative **road layout designs** for new urban developments
- Optimization of **intersection placement and spacing**

- Identification of **bottleneck-prone zones** in proposed networks
- Cost-effective expansion strategies for growing cities

Benefits

- Rapid exploration of thousands of design possibilities
- Data-driven network layouts rather than heuristic planning
- Integration with GIS and BIM platforms for visualization

Traffic Prediction and Scenario Simulation

Transportation planners must anticipate how networks behave under normal and abnormal conditions. Generative AI enables simulation of realistic **what-if scenarios** that may be rare or not yet observed.

Diffusion models and GANs trained on historical traffic time-series can generate:

- Peak-hour congestion patterns
- Accident-induced traffic disruptions
- Effects of road closures or construction diversions
- Festival, event, or emergency evacuation traffic surges

Planning Applications

- Testing robustness of signal timing plans
- Designing diversion routes during road maintenance
- Emergency response and evacuation planning
- Evaluating congestion pricing strategies

Generative simulations provide planners with **future traffic states** rather than simple point forecasts.

Autonomous and Connected Vehicles Planning

With the rise of Autonomous Vehicles (AVs) and Connected Vehicle (CV) technologies, planners must understand how vehicles interact with infrastructure, pedestrians, and each other.

Generative AI can simulate complex interactions among:

- AVs, human-driven vehicles, cyclists, and pedestrians
- Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication

- Mixed traffic environments during technology transition phases

Applications

- Testing AV behavior at intersections and roundabouts
- Evaluating infrastructure requirements for V2I systems
- Simulating platooning and cooperative driving scenarios
- Planning dedicated AV lanes and smart corridors

These simulations help planners design infrastructure ready for future autonomous mobility ecosystems.

Smart City and Multimodal Transport Integration

Modern cities require seamless integration of multiple transport modes—bus, metro, paratransit, cycling, and walking. Generative models help simulate how people shift across modes and how networks interact spatially and temporally.

Capabilities

- Modeling passenger flow between metro stations, bus stops, and sidewalks
- Generating multimodal trip chains (walk → bus → metro → walk)
- Identifying gaps in first-mile and last-mile connectivity
- Simulating effects of introducing bike-sharing or e-scooters

Planning Benefits

- Designing integrated transit hubs
- Optimizing schedules across modes
- Improving accessibility and reducing total travel time
- Supporting sustainable and low-carbon mobility planning

ADVANTAGES OF USING GENERATIVE AI IN TRANSPORTATION PLANNING

Generative AI introduces a paradigm shift in how transportation systems are analyzed, designed, and planned. By learning from existing datasets and producing realistic synthetic data, scenarios, and simulations, generative models overcome many limitations of traditional planning approaches that depend heavily on costly field data, static assumptions, and limited scenario testing.

1. Reduces Dependency on Real Data Collection

Transportation data collection through surveys, sensors, cameras, and GPS devices is expensive, time-consuming, and often constrained by privacy regulations. In many regions, especially developing cities, reliable and continuous traffic data is simply unavailable.

Generative AI can learn patterns from limited datasets and produce **high-quality synthetic traffic, mobility, and demand data** that preserve the statistical properties of real observations.

Impacts:

- Minimizes repeated field surveys and sensor deployment
- Provides data for regions with poor sensing infrastructure
- Preserves privacy by avoiding use of identifiable traveler data
- Enables researchers to work with large datasets without legal restrictions

2. Enables Scenario-Based Planning

Traditional transportation models often evaluate only a few predefined scenarios due to modeling complexity and data limitations. Generative AI enables planners to create and test **hundreds of realistic what-if scenarios**.

Examples include:

- Population growth or migration patterns
- Introduction of new metro or BRT corridors
- Road closures, construction diversions, or accident events
- Policy changes such as congestion pricing or parking restrictions
- Emergency evacuation or festival traffic conditions

Impacts:

- Better preparedness for rare and extreme events
- Risk-free evaluation of policies before implementation
- Increased resilience of transportation networks

3. Improves Accuracy of Demand Forecasting

Travel demand is influenced by uncertain human behavior, socio-economic factors, and emerging mobility trends. Generative models such as VAEs and diffusion models capture this uncertainty by learning probabilistic travel patterns.

Impacts:

- More realistic Origin–Destination (OD) matrices
- Better prediction of mode shifts (private car to public transit)
- Improved ridership forecasts for new transport systems
- Reduced forecasting bias caused by limited historical data

4. Assists in Visualization of Future Transport Networks

Generative AI can create visual and spatial representations of proposed road layouts, traffic states, and multimodal interactions. When integrated with GIS, BIM, and simulation platforms, these outputs become powerful visualization tools.

Impacts:

- Clear visualization of proposed road network designs
- Animated simulations of congestion and traffic flow
- Better communication of plans to stakeholders and the public
- Support for participatory planning and decision transparency

5. Supports Decision Makers with Intelligent Insights

Beyond data generation, generative AI (especially when combined with LLMs and analytics tools) helps interpret complex datasets and produce actionable insights for planners and policymakers.

Impacts:

- Automated generation of planning reports and summaries
- Interpretation of traffic patterns and anomaly detection
- Policy analysis support using simulated evidence
- Faster, data-driven decision-making processes

CHALLENGES AND LIMITATIONS

Despite advantages, there are few issues:

- Requirement of large training datasets

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- Lack of interpretability of deep models
- Ethical concerns in synthetic data use
- High computational requirements
- Need of domain expertise for implementation

CASE STUDIES FROM LITERATURE

Table: 2

Study	Area	Model	Outcome
Traffic simulation in Beijing	Urban traffic	GAN	Realistic congestion patterns
Demand modelling in New York	Public transport	VAE	Improved demand accuracy
Road layout planning	Smart cities	GAN	Multiple optimized layouts

INTEGRATION WITH EXISTING PLANNING TOOLS

Generative AI can be integrated with GIS, BIM, and traffic simulation software like VISSIM, SUMO and TransCAD for better results.

FUTURE RESEARCH DIRECTIONS

- Hybrid generative and reinforcement learning models
- Real-time generative traffic forecasting
- Ethical AI frameworks in transportation
- Integration with IoT and digital twins

DISCUSSION

Generative AI is still in early stage for transportation planning but showing promising results. It provides new perspective to planners for visualizing complex systems. With improvement in computing and data availability, its adoption will increase.

CONCLUSION

Generative AI has potential to revolutionize transportation planning by enabling realistic simulations, synthetic data generation and intelligent decision support. Although challenges related to interpretability, data quality and ethics remains, continuous research can overcome these issues. Generative AI will become an important tool for future smart and sustainable transportation systems.

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