Thesis Proposal for MPhil Degree

Student Name:	Songxin LEI
ID Number:	50018198
Group Project:	Connected Transportation Information System(CTIS)
Project Manager:	Wenxun Hu
Project Supervisor:	Wenxun Hu
Individual Project:	Collaborative Public Resource Allocation: A Spatio-temporal Feature Extraction and Potential Game-Based Reinforcement Learning Framework
Thesis Supervisor(s):	Yuxuan Liang
Student's Thrust & Hub:	Data Science and Analysis Thrust & Information Hub

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Part I Introduction to the Group Project

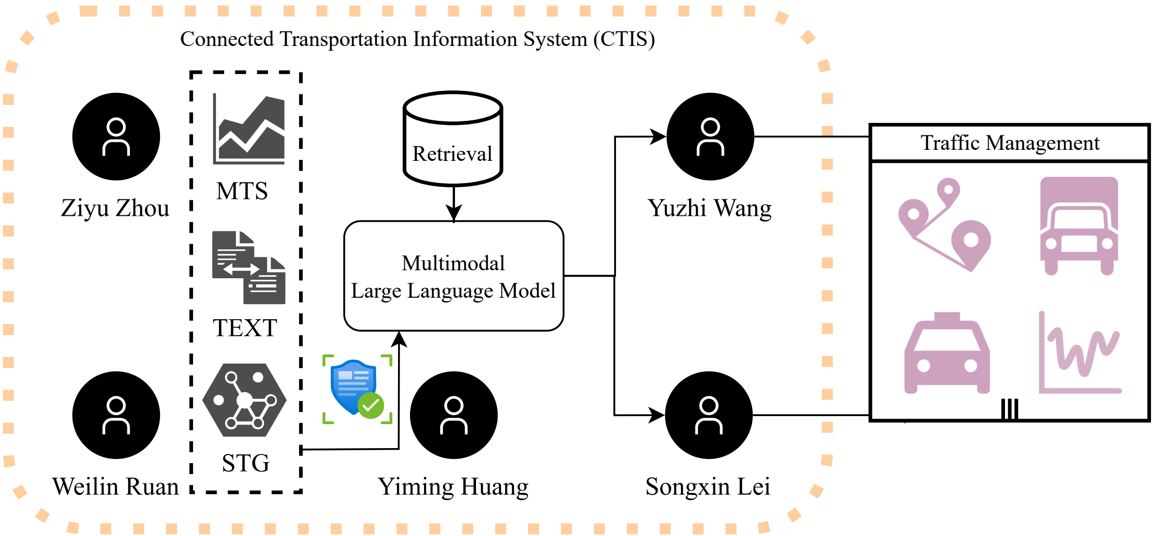

Figure 1: The outline of the composition and structure of our group project.

1.1 Background and Objective

The rapid urbanization of modern cities has created significant challenges for urban transportation systems. With increasing population densities, urban areas are grappling with issues such as traffic congestion, delays, safety hazards, and environmental degradation. These challenges not only reduce the efficiency of transportation networks but also threaten public safety and hinder sustainable urban development. Addressing these issues requires innovative, intelligent solutions that harness the power of modern technologies.

Intelligent Transportation Systems (ITS) have emerged as a transformative approach to modernizing transportation management. ITS combines advanced technologies in sensing, communication, and data analysis to create smarter, more adaptive transportation frameworks. By utilizing real-time traffic monitoring, predictive analytics, and connected vehicle technologies, ITS seeks to optimize traffic flow, enhance safety, and promote sustainability. ITS spans multiple key areas, including traffic management, autonomous vehicle support, infrastructure monitoring, and multimodal data fusion for urban planning.

Building on this vision, our group project, Connected Transportation Information System (CTIS), aims to develop an integrated platform that combines real-time traffic data, Vehicle-to-Everything (V2X) communication, and predictive analytics. This platform is designed to tackle critical challenges in urban transportation systems, offering innovative solutions to optimize traffic flow, enhance road safety, and reduce environmental impact.

Urban transportation systems face numerous pressing challenges. The increasing demand for traffic in urban areas has led to severe congestion and delays, which disrupt daily commutes and cause significant economic losses. Safety remains a key concern, with a lack of real-time hazard detection and preventive measures contributing to frequent accidents. Additionally, inefficient route planning and traffic management exacerbate energy consumption and carbon emissions, worsening environmental degradation. Notable recent incidents, such as the landslide on the Meizhou Meida Expressway in May 2024 and the Lixinsha Bridge collapse caused by a container ship collision in February 2024, highlight the urgent need for intelligent systems capable of preventing such disasters and improving emergency response capabilities.

To address these challenges, the CTIS project adopts a comprehensive, interdisciplinary approach. The project focuses on integrating real-time communication and data-sharing systems to facilitate seamless interactions between vehicles, infrastructure, and management centers. Predictive analytics and machine learning technologies will be used to analyze dynamic traffic patterns, detect potential hazards, and provide actionable insights to optimize traffic flow. Additionally, the project incorporates V2X communication technologies to enhance connectivity and support autonomous vehicle operations, while multimodal data fusion will enable urban planners to make more informed decisions for long-term mobility solutions.

The CTIS project is structured to achieve the following key objectives:

1. **Real-time Traffic Optimization:** Develop advanced algorithms for intelligent traffic management to reduce congestion and delays.

2. **Safety Enhancement:** Integrate V2X communication technologies and real-time monitoring to improve hazard detection and accident prevention capabilities.

3. **Sustainability Promotion:** Facilitate efficient route planning and traffic management to reduce energy consumption and carbon emissions.

4. **Urban Mobility Support:** Utilize multimodal data fusion to generate actionable insights for urban planning and decision-making.

1.2 Significance

The CTIS project is a transformative initiative that addresses critical challenges in urban transportation systems while laying the foundation for the long-term evolution of Intelligent Transportation Systems (ITS). Its significance lies in its ability to integrate cutting-edge sensing, communication, and data analytics technologies, creating smarter, safer, and more sustainable transportation networks. By combining these technologies, CTIS not only provides solutions to immediate urban mobility challenges but also prepares cities for the adaptive demands of future, technology-driven urban environments.

The significance of the project can be summarized as follows:

- **Reducing Congestion and Improving Efficiency:** By leveraging real-time traffic data and predictive algorithms, CTIS optimizes traffic flow, reduces delays, and enhances the overall efficiency of urban transportation systems, ensuring smoother commutes and improved accessibility.
- **Improving Road Safety:** Through the integration of connected vehicle technologies and real-time hazard detection, CTIS enhances road safety by reducing the risk of accidents and providing timely alerts, benefiting all road users, including pedestrians and cyclists.
- **Promoting Environmental Sustainability:** The project facilitates efficient route planning and traffic management, which reduces fuel consumption and carbon emissions, contributing to global efforts to mitigate climate change and promoting sustainable urban mobility.
- **Advancing Urban Planning:** CTIS generates multimodal, data-driven insights that help urban planners design smarter, more resilient cities, guiding long-term infrastructure development and ensuring sustainable growth.
- **Driving Technological Innovation:** The CTIS project fosters innovation in transportation research by developing scalable, adaptable solutions that can be applied to diverse urban settings worldwide, advancing the field of ITS and contributing to the development of next-generation transportation systems.

In addition to addressing immediate challenges such as congestion, safety, and environmental concerns, CTIS provides a scalable framework for intelligent transportation management that can evolve with the changing needs of urban populations. Its holistic approach ensures that the project serves not only as a solution to current transportation problems but also as a foundation for the continuous advancement of ITS. By promoting smarter traffic systems and supporting sustainable urban mobility, CTIS plays a pivotal role in shaping the future of urban transportation—an adaptive, environmentally responsible, and technology-driven future.

1.3 Project Composition

The CTIS project is composed of a series of interconnected individual projects, each contributing unique insights and technological advancements. Together, these subprojects form a comprehensive and integrated approach to addressing urban transportation challenges. The key components of the project are as follows:

1. Weilin Ruan: **Retrieval-Augmented Universal Models for Spatio-Temporal Data**
   Weilin Ruan's project focuses on developing Retrieval-Augmented Universal Models for Spatio-Temporal Data, which aims to design a highly efficient framework for integrating and processing large-scale spatio-temporal datasets. As urban data from diverse sources such as satellite imagery, traffic sensors, and public transit records continue to grow, effectively analyzing this data in a unified and scalable manner becomes increasingly challenging. This project addresses these challenges by leveraging retrieval-augmented techniques, which enhance both the performance and interpretability of spatio-temporal data models, thus providing a more effective foundation for the overall CTIS system.

2. Ziyu Zhou: **Frequency-Enhanced Lightweight Framework for Multivariate Time Series Forecasting**
   Ziyu Zhou's project focuses on the development of WaveTS, a lightweight, wavelet-based time series forecasting model tailored for traffic prediction within the CTIS framework. By decomposing multivariate traffic data into multiple frequency scales, WaveTS captures both global patterns and localized fluctuations, ensuring accurate and efficient forecasts. This approach supports real-time congestion forecasting, facilitates seamless edge deployment, and enhances safety measures. Ziyu's work strengthens the CTIS framework by providing timely and reliable traffic predictions, thereby improving the overall efficiency and safety of the transportation system.

3. Yiming Huang: **Hallucination Detection and Mitigation, Robustness Evaluation, and Multi-Source Information Debiasing**

   Yiming Huang's research focuses on developing methods to address safety and reliability within the CTIS framework. His work involves creating more robust models by mitigating hallucinations—errors in AI-generated information—through improved interpretability and multi-source data integration. By addressing these issues, Yiming's sub-project ensures that the CTIS system can rely on accurate, debiased data, particularly when integrating information from various sources. Additionally, his contributions provide methods for evaluating system performance, ensuring robustness, and improving the safety and trustworthiness of the CTIS framework.

4. Yuzhi Wang: **Large Language Model Enhanced Urban Agent Simulation and Application**

   Yuzhi Wang's project leverages large language models (LLMs) to enhance agent-based urban simulations, especially for modeling individual decision-making behaviors. By using LLM technologies such as prompt generation, retrieval, and fine-tuning, Yuzhi's work focuses on generating human-centered agent behaviors in urban environments—such as mobility, economic, and social interactions. This project provides micro-level insights into urban evolution and optimization, including areas like point of interest (POI) mapping, land-use, and transportation infrastructure development, thereby enriching the CTIS framework with valuable simulation-driven perspectives.

5. Songxin Lei: **Collaborative Public Resource Allocation: A Spatio-temporal Feature Extraction and Potential Game-Based Reinforcement Learning Framework**

   Songxin Lei's work focuses on ensuring that mobile public resources, such as intelligent trash bins and delivery stations, are deployed effectively to maximize coverage and meet dynamic demand. This project integrates spatio-temporal feature extraction techniques with reinforcement learning, using potential game theory to model the collaborative relationships among multiple agents. By constructing a robust reward function based on spatio-temporal dynamics, the project provides actionable decision-making strategies that optimize resource allocation. The outcomes contribute to the development of a scalable, adaptive, and intelligent transportation system, offering critical insights for urban planners and policymakers to enhance urban mobility and resource efficiency.

Together, these interconnected projects create a holistic and integrated approach to solving the challenges of urban transportation, particularly in the context of sustainable mobility, safety, and efficiency. By addressing the diverse aspects of urban mobility, the projects ensure that the CTIS framework is adaptable, scalable, and capable of driving innovation in future urban transportation systems.

1.4 Project Connections

Each individual project within the Connected Transportation Information System (CTIS) interlinks seamlessly to create a cohesive and efficient system. The contributions of each sub-project enhance the overall performance and adaptability of the platform:

- **Weilin's Predictive Analysis:** Weilin Ruan's project plays a pivotal role in the synergy of CTIS. The retrieval-augmented framework developed in this project enhances the efficiency of integrating and processing large-scale spatio-temporal datasets. By dynamically retrieving and integrating historical and real-time data, Weilin's work provides a solid foundation for downstream tasks. Specifically, it supports Ziyu Zhou's temporal models by supplying contextually relevant historical data, such as traffic patterns under similar conditions, which significantly improves the accuracy and robustness of time series predictions. The spatio-temporal graph representations generated by Weilin's project are also key inputs for Songxin Lei's infrastructure planning, enabling better optimization of connected infrastructure such as smart traffic lights and vehicle-to-infrastructure (V2I) communication systems. Additionally, these models assist Yuzhi Wang's work on autonomous vehicle trajectory predictions by providing cross-city generalization capabilities, improving the safety and reliability of autonomous navigation.
- **Ziyu's Strategic Deployment:** Ziyu Zhou's project focuses on modeling multivariate time series (MTS) data within the CTIS ecosystem. The time series forecasts generated by Ziyu's models serve as a vital input stream for tasks such as route optimization, demand forecasting for shared mobility services, and resource allocation for charging stations. These forecasts enrich the overall data pool, including spatio-temporal graphs (STG) and sensor-derived metrics, ensuring the

entire CTIS framework benefits from accurate and timely predictions. Ziyu's contributions enhance the decision-making capabilities and responsiveness of the interconnected urban transportation network.

- **Yiming's Securing Measures:** Yiming Huang's research focuses on safety and robustness within the CTIS framework. His work addresses three key areas: 1) By passing LLM-extracted text information to various CTIS modules, inherent hallucination issues may arise. Yiming's research helps mitigate these issues, ensuring the accuracy of inputs and outputs for Weilin, Ziyu, and Yuzhi's modules. 2) Yiming also provides methods to test the robustness of the system against noise in input data, ensuring the system's stability, especially in Songxin's and Yuzhi's modules. 3) Lastly, Yiming works on AI debiasing to ensure that CTIS does not overly rely on biased data sources, promoting a balanced and efficient use of multi-source information within the framework.
- **Yuzhi's Simulation Insights:** Yuzhi Wang's project leverages large language models (LLMs) to create a digital twin environment for CTIS through generative agent-based modeling (GABM). Yuzhi's work uses spatio-temporal data, particularly trajectory data, to build and simulate urban agents, offering insights into urban mobility and infrastructure. This simulation environment serves as a powerful tool for optimizing transportation systems and guiding future urban planning and evolution. The LLM-based approach enhances the CTIS framework by providing a flexible, scalable, and interactive environment for simulating real-world urban scenarios.
- **Songxin's Allocation Strategies:** Songxin Lei's research focuses on the fine-grained decision-making aspect of the CTIS framework. By leveraging predictive insights from Ziyu and Weilin—such as time-series population flow predictions and spatio-temporal graph forecasts—Songxin develops strategies for deploying mobile public resources. These strategies are optimized to interact with the environment and convert predictive insights into actionable decisions, maximizing the real-world impact of the CTIS system.

1.5 Project Milestones

The development of the Connected Transportation Information System (CTIS) is structured into four key phases, each focused on ensuring the seamless integration of individual sub-projects into a unified, scalable system. These milestones cover data collection, model development, collaborative integration, platform testing, and deployment.

1. **Individual Data Collection and Model Development (Months 0-3)**
   - **Focus:** At this stage, each team member collects and processes data relevant to their specific sub-project within the CTIS framework.
   - **Key Activities:**
     - Develop initial models and algorithms for tasks such as:
       * Traffic flow modeling and congestion analysis.
       * Optimizing charging infrastructure for electric vehicles.
       * Scheduling algorithms for shared-mobility services.
       * Autonomous vehicle behavior predictions.
       * Spatio-temporal urban analysis for transportation planning.
     - Refine datasets to ensure consistency and compatibility across sub-projects.
2. **Collaborative Data Integration and Model Alignment (Months 3-6)**
   - **Focus:** This phase emphasizes collaboration among team members to integrate individual datasets and align models within the CTIS framework.
   - **Key Activities:**
     - Share datasets and combine insights from sub-projects, such as traffic modeling, urban analysis, and autonomous vehicle behavior predictions.
     - Synchronize predictive models, optimization techniques, and scheduling algorithms to ensure smooth data flow and system compatibility.
     - Establish a unified data pipeline to handle multimodal spatio-temporal data efficiently.
3. **Holistic Platform Integration and Initial Testing (Months 6-9)**
   - **Full Platform Integration:**
     - Integrate components developed during earlier phases into a unified CTIS platform.
     - Consolidate features such as traffic prediction, charging infrastructure optimization, shared mobility scheduling, autonomous behavior analysis, and urban transportation insights.

- **Initial Testing and Evaluation:**
  - Conduct initial testing in simulated environments to ensure the platform operates cohesively.
  - Test the platform in diverse urban scenarios to evaluate its adaptability and robustness.

4. **Comprehensive Deployment and Future Planning (Months 9-12)**
   - **Deployment in Selected Areas:**
     - Roll out the integrated CTIS platform in selected urban areas as pilot projects.
     - Collect feedback and performance metrics to refine system components and improve operational efficiency.
   - **Citywide or Multi-Area Deployment:**
     - Scale up the system for full deployment across cities or regions based on the success of pilot projects.
     - Ensure the platform's scalability to address diverse urban mobility challenges.
   - **Project Summary and Future Development:**
     - Compile a comprehensive project report documenting key achievements, challenges, and lessons learned.
     - Propose future development plans to enhance the CTIS platform, incorporating emerging technologies and addressing evolving urban mobility needs.

CTIS Project Milestones and Development Phases

Phase	Description and Key Activities
Phase 1: Individual Data Collection and Model Development (Months 0-3)	

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CTIS Project Milestones and Development Phases (Continued)

Data Collection and Initial Model Development	• Collect and process data for sub-projects. • Develop initial models and algorithms for: – Traffic flow modeling and congestion analysis. – Charging infrastructure optimization for EVs. – Scheduling algorithms for shared mobility services. – Autonomous vehicle behavior predictions. – Spatio-temporal urban analysis. • Ensure dataset consistency across sub-projects.
Phase 2: Collaborative Data Integration and Model Alignment (Months 3-6)	
Collaborative Data Integration	• Integrate datasets and align models within CTIS. • Synchronize predictive models and scheduling algorithms. • Establish a unified pipeline for spatio-temporal data.
Phase 3: Holistic Platform Integration and Initial Testing (Months 6-9)	
Platform Integration and Testing	• Integrate components into a unified CTIS platform. • Conduct platform testing in simulated environments. • Test in diverse urban scenarios to evaluate adaptability.
Phase 4: Comprehensive Deployment and Future Planning (Months 9-12)	

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CTIS Project Milestones and Development Phases (Continued)

Deployment and Expansion	• Deploy CTIS platform in selected areas as pilot projects. • Collect performance feedback and refine system components. • Scale deployment across cities or regions. • Compile a comprehensive project report and propose future development.

Part II Proposal of the Individual Project

2.1 Significance and Relevance of the Individual Project to the Group Project

2.1.1 Complementary Role

The group project aims to establish an intelligent, safe, and efficient interconnected smart transportation system that maximizes service coverage for population flows. My research complements this objective by focusing on the dynamic allocation and collaborative scheduling of mobile public resources, such as intelligent mobile trash bins and smart delivery stations. By leveraging the spatio-temporal distribution of predicted population flows and resource demands, my work develops decision-making algorithms that optimize resource deployment. This bridges the gap between theoretical forecasting and practical implementation, ensuring effective utilization of resources within the smart transportation framework.

2.1.2 Value Addition

The project contributes significantly to the overall group initiative by:

1. **Bridging Predictions with Real-world Deployment**: The project acts as a critical link between population flow predictions and practical applications, enabling the deployment of mobile public resources. This ensures that theoretical results are transformed into actionable impacts on human productivity and daily life.

2. **Reinforcing Intelligence through Adaptive Learning**: By employing reinforcement learning algorithms, the project allows agents to autonomously learn

through interactions with the environment. This self-adaptive process maximizes resource utilization to serve more population flows, aligning with the core principles of smart systems.

3. **Enhancing Resilience via Multi-agent Coordination**: The project studies scenarios where multiple agents collaboratively serve shared population flows. By modeling competitive relationships and balancing individual needs to maximize group utility, the research strengthens the elasticity and robustness of the intelligent transportation system.

The combined contributions of deployment, adaptive learning, and multi-agent collaboration enhance the group's efforts to establish a more intelligent, flexible, and resilient urban mobility system. This work is essential in bridging theoretical research with practical implementation to achieve the overarching goals of the group project.

2.1.3 Interdependence

The success of my individual project is closely tied to the contributions of other components within the group project. My research occupies a pivotal position in the workflow, bridging predictive analysis and downstream assessments:

1. **Preceding Contributions**: Before my project, teammates focus on processing and predicting time-series and spatio-temporal graph data. These predictions provide the foundational input for my research, offering insights into population flow and resource distribution dynamics.

2. **Core Role in Decision-making**: My project serves as the decision-making layer, utilizing the predictive outcomes and extracted features to deploy intelligent decision-making algorithms. This ensures that predictions are translated into actionable deployments, maximizing their real-world impact on production and daily life.

3. **Support for Subsequent Components**: The outputs of my project provide a practical basis for integrating Large Language Models (LLMs) to enhance predictive accuracy and offer a foundation for evaluating the safety and robustness of the system. By connecting predictive insights with practical application, my project establishes a solid framework for these subsequent enhancements.

This interdependent structure highlights my project's role in linking theoretical predictions with practical deployment while enabling seamless collaboration with other components, thereby strengthening the overall effectiveness of the intelligent transportation system.

2.2 Statement of the Individual Project in Details

2.2.1 Literature/Market Review and Problem Definition

The allocation and scheduling of public resources in the context of smart cities remains an underexplored research area. Existing studies can be broadly categorized into static and dynamic public resource management. Static studies focus on the location [1] and deployment [2] of immovable resources [3], whereas dynamic studies explore the scheduling [4] and path planning [5] of mobile resources. Dynamic resource scheduling problems are often modeled as NP-hard, and many studies rely on heuristic algorithms to find approximate solutions [6]. However, these approaches face several key limitations: they frequently overlook the temporal and spatial dynamics of population flows, assume isolated service zones for individual resources, and fail to consider the collaborative interactions among multiple resources in serving a shared area.

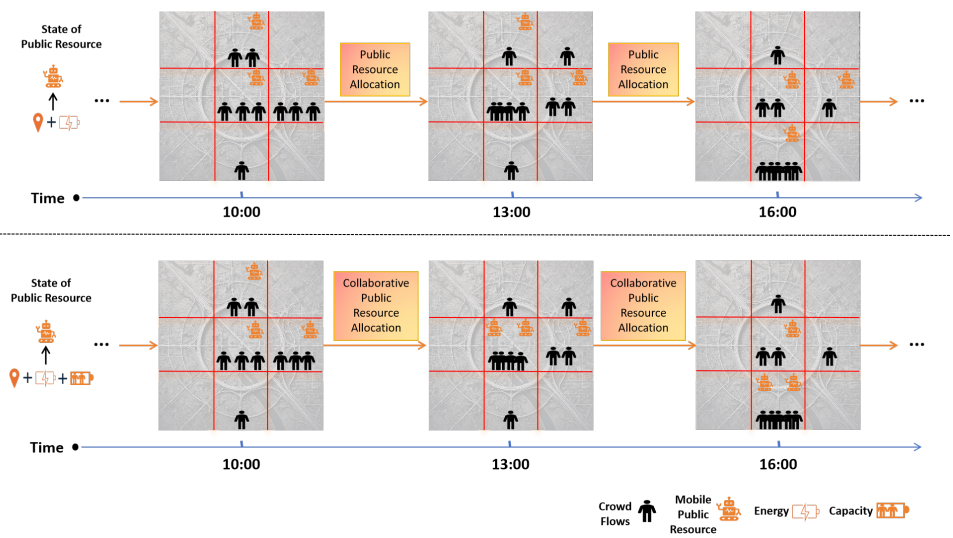

Figure 2: Collaborative Public Resource Allocation vs. Public Resource Allocation.

Building on these observations, we identify critical gaps and define the scope of the research problem, as shown in Figure 2. First, existing studies fail to address scenarios where multiple public resources collaboratively serve a single area. In real-world settings, each resource has limited service capacity, and their overlapping service areas necessitate the study of collaborative scheduling among multiple agents. This consideration is essential for capturing the complexity of smart city environments. Second, when making scheduling decisions, future population flow distributions are typically unknown. Incorporating predictions of future distributions into the decision-making framework is therefore crucial. Using these predictions as training data enables the development of robust scheduling models that are better aligned with real-world conditions. Third, the temporal and spatial dynamics of population flows present additional challenges. Capturing these dynamic spatio-temporal features and embedding them effectively into the decision framework is vital for improving scheduling accuracy and responsiveness. Finally, collaborative interactions among multiple agents require a formal mathematical representation. Investigating whether these relationships can be modeled appropriately within an established mathematical framework, such as game theory, provides a strong foundation for solving the scheduling problem.

In summary, the research problem focuses on addressing the gaps in collaborative scheduling, incorporating predictive data for future population flows, capturing spatio-temporal dynamics, and developing a mathematical model for agent interactions. These considerations define the foundation for studying collaborative public resource allocation in smart city environments.

2.2.2 Objective and Scope of the Project

The objectives and scopes of this project include:

1. **Modeling Collaborative Interactions**: The project models the interaction among multiple mobile public resources as a game-theoretic problem. By treating these resources as agents in a game, we analyze the collaboration dynamics and investigate desirable mathematical properties, such as stability and equilibrium.

2. **Developing a Reinforcement Learning Framework**: The project proposes a reinforcement learning framework where each public resource is treated as an agent with the ability to autonomously explore the environment and make allocation decisions. This framework ensures adaptive and optimized resource deployment in dynamic scenarios.

3. **Incorporating Spatio-temporal Features**: To address the temporal and spatial dynamics of population flow distributions, the project employs advanced neural network architectures to capture and embed these features. These embeddings

are integrated into the reinforcement learning framework to construct a reward function, ensuring the model effectively adapts to environmental changes.

4. **Establishing Baseline Comparisons**: The project implements a heuristic algorithm-based baseline to evaluate the performance of the proposed reinforcement learning framework. Comparative analysis demonstrates the superiority and robustness of the proposed approach in managing complex and dynamic public resource allocation scenarios.

2.2.3 Research Method and Justification

To provide a theoretical foundation for modeling collaborative public resource allocation, improve the efficiency of the reinforcement learning framework, and enhance the capture of spatio-temporal dynamics, we propose an integrated framework that combines potential game theory, the Actor-Critic (A2C) reinforcement learning algorithm, and neural networks for spatio-temporal feature extraction. Our method represents the first reinforcement learning framework proposed in this domain and introduces a potential game-driven reinforcement learning approach, offering significant insights into the intersection of AI and collaborative resource scheduling.

1. **Integer Programming Modeling**: The problem is initially formulated as a 0-1 integer programming problem, which is a standard approach for resource allocation scenarios. However, integer programming is NP-hard, making exact solutions infeasible within polynomial time. Consequently, heuristic or AI-based algorithms are required to approximate solutions efficiently.

2. **Potential Game Modeling**: Each public resource is treated as a player, and the integer programming problem is reinterpreted as a non-cooperative game among multiple players, where each player seeks to maximize its long-term coverage of population flows. By constructing a potential function for the system and individual reward functions for each player, the game is further modeled as a potential game. The favorable properties of potential games, such as the strong correlation between the potential function and the system's efficiency, enable us to design a reinforcement learning reward function based on the potential function, ensuring a theoretically grounded approach to achieving globally optimal resource allocation.

3. **Reinforcement Learning Algorithm**: Each player is modeled as an agent in a reinforcement learning framework, implemented using the A2C algorithm. The state is defined as a triplet of location, energy, and service capacity, while the action corresponds to selecting a deployment location. The reward function is constructed based on the potential function derived from the game model. To ensure realistic operations, such as starting and ending at charging stations, we introduce an energy masking operation.

4. **Spatio-temporal Embedding**: To account for the dynamic nature of population flows, we experiment with spatio-temporal feature extraction components, such as DCRNN, to identify the most suitable architecture for our framework. These embeddings capture the temporal and spatial dynamics of population distributions and are incorporated into the reward function to achieve optimal performance across both time and space.

5. **Experiments**: To evaluate the proposed reinforcement learning framework, we implement a heuristic algorithm as a baseline for comparison. Experiments are conducted on two datasets: Happy Valley and Beijing Taxi. Results demonstrate that our approach achieves state-of-the-art (SOTA) performance compared to the baseline, highlighting its effectiveness in collaborative public resource scheduling. Furthermore, the framework and implementation will be open-sourced to encourage further research in this domain.

2.2.4 Execution Plan

The execution plan for this project is structured into several critical phases to ensure the systematic development and evaluation of the proposed framework:

1. **Development and Refinement of Integer Programming and Game Models**: This phase focuses on modeling the collaborative public resource allocation problem as a 0-1 integer programming problem. The model will then be reformulated as a potential game by constructing the system's potential function and individual agents' reward functions. This provides the theoretical foundation for subsequent reinforcement learning implementation.

2. **Design and Implementation of Reinforcement Learning Framework**: Using the Actor-Critic (A2C) algorithm, this phase involves designing a reinforcement

learning framework where each public resource is modeled as an intelligent agent. The state (location, energy, and service capacity) and action (deployment location) are defined, and the reward function is constructed based on the potential function derived from the game model.

3. **Integration of Spatio-temporal Embeddings**: This phase incorporates advanced spatio-temporal feature extraction techniques, such as DCRNN, into the reinforcement learning framework. These embeddings capture the dynamic nature of population flows and enhance the framework's decision-making capabilities.

4. **Experimentation and Baseline Comparisons**: The proposed framework will be evaluated using real-world datasets, such as Happy Valley and Beijing Taxi. A heuristic algorithm-based baseline will be implemented for comparison to validate the performance of the reinforcement learning framework. Results will assess the effectiveness and superiority of the proposed method.

5. **Validation and Dissemination**: The adaptability and effectiveness of the framework will be validated across diverse scenarios. Experimental findings and methodologies will be documented for publication in relevant journals and conferences. The framework will also be open-sourced to encourage further research and development in this domain.

This phased execution plan ensures a comprehensive and rigorous approach to addressing the collaborative public resource allocation problem, bridging theoretical modeling and practical implementation.

2.2.5 Intended Outcomes

Outcome 1: Enhanced Collaborative Resource Allocation Modeling

This project aims to provide a novel theoretical foundation for collaborative public resource allocation in smart cities. By modeling the problem as a potential game and integrating spatio-temporal dynamics, the project offers a mathematically rigorous approach to analyzing and optimizing resource deployment. This enhanced modeling framework ensures more effective coordination among multiple resources, addressing the complexities of real-world scenarios.

Outcome 2: Reinforcement Learning Framework Innovation

The project introduces a reinforcement learning framework tailored to collaborative resource scheduling. By incorporating the Actor-Critic algorithm and spatio-temporal embeddings, the framework enables autonomous agents to learn optimal strategies for dynamic resource allocation. The use of a potential game-driven reward function ensures convergence to globally optimal solutions, setting a new standard for AI-based resource scheduling.

Outcome 3: Benchmark Results and Practical Validation

Through experiments on real-world datasets, such as Happy Valley and Beijing Taxi, the project demonstrates the superiority of the proposed reinforcement learning framework compared to heuristic baselines. Results validate the practical applicability of the framework, showcasing its potential for achieving state-of-the-art performance in dynamic public resource allocation scenarios. The open-source release of the framework further facilitates its adoption and application in future research.

In summary, the outcomes of this project—including Enhanced Collaborative Resource Allocation Modeling, Reinforcement Learning Framework Innovation, and Benchmark Results and Practical Validation—contribute significantly to advancing the integration of AI in collaborative resource scheduling. This project not only addresses theoretical and practical challenges but also provides a scalable solution for intelligent public resource management in smart cities.

2.3 Project Milestones

The milestones of my individual project, Collaborative Public Resource Allocation: A Spatio-temporal Feature Extraction and Potential Game-Based Reinforcement Learning Framework, are outlined as follows:

Milestone 1: Data Collection and Preprocessing (Current - 1 month)

- Collect relevant urban mobility data, including predictive time-series data and spatio-temporal graph data, as provided by the group project.
- Preprocess the data to ensure quality, consistency, and compatibility with the framework's requirements.
- Ensure that data inputs align with the group's model outputs for seamless integration into the overall system.

Milestone 2: Model Development and Integration (1 month - 3 months)

- Develop and refine the reinforcement learning model, based on the A2C algorithm, for resource allocation.
- Integrate spatio-temporal embeddings into the model to capture population flow dynamics and improve decision-making.
- Align the model with group-level predictive outputs for resource scheduling.
- Collaborate with the group to ensure compatibility with shared data and models.

Milestone 3: Collaborative Integration and Platform Alignment (3 months - 6 months)

- Integrate the collaborative resource allocation model with the group's urban mobility framework.
- Ensure smooth data flow and synchronization with predictive models from traffic flow and charging infrastructure optimization.
- Test the integrated model with real-world datasets, ensuring compatibility and proper function within the CTIS platform.
- Align deployment strategies for mobile public resources with the broader urban mobility planning and scheduling algorithms developed by the group.

Milestone 4: Testing, Validation, and System Evaluation (6 months - 9 months)

- Validate the model's adaptability and performance through testing in various urban scenarios and with different population distribution datasets.
- Collaborate with group members to evaluate the model's efficiency in real-world settings and ensure its scalability across diverse cities.
- Collect feedback from pilot tests to fine-tune resource allocation strategies.

Milestone 5: Comprehensive System Deployment and Future Integration (9 months - 12 months)

- Deploy the integrated collaborative public resource allocation model in selected urban areas as pilot projects.
- Scale up deployment based on feedback and performance metrics from the pilot phase.

- Document the integration process and future recommendations for extending the platform across multiple regions.
- Ensure alignment with the group's long-term goals for intelligent and sustainable urban mobility.

The alignment between the individual and group project milestones

Milestone	Collaborative Public Resource Allocation (Individual Project)	Connected Transportation Information System (Group Project)
Phase 1: Technology Development and Integration		
Milestone 1: Data Collection and Preprocessing	Collect and preprocess time-series and spatio-temporal data for resource allocation.	Data collection and model development in each member's area, with a focus on urban mobility and transportation data.
Phase 2: System Optimization and Expanded Testing		
Milestone 2: Model Development and Integration	Develop reinforcement learning model and integrate spatio-temporal embeddings for decision-making.	Integration of individual models and data sources, including predictive traffic flow and charging optimization. Initial system testing.
Phase 3: Pilot Projects and Field Evaluation		
Milestone 3: Collaborative Integration and Platform Alignment	Integrate the resource allocation model with group's urban mobility framework. Test with real-world datasets.	Collaborative data integration, testing, and system alignment among team members. Validation of integrated models and system effectiveness.
Phase 4: Final Deployment and Project Summary		

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The alignment between the individual and group project milestones (Continued)

Milestone 4: Testing, Validation, and System Evaluation	Validate model performance in urban scenarios, gather feedback for improvements.	Deployment in selected areas for pilot projects. Evaluation of system performance based on real-world data.
Milestone 5: Comprehensive System Deployment and Future Integration	Final deployment of the model and integration into selected urban areas.	Full deployment across urban areas, scaling based on pilot performance. Integration with long-term urban mobility strategies.

2.4 Budget Plan

2.4.1 Estimated Budget

The estimated budget for my individual project, "Collaborative Public Resource Allocation: A Spatio-temporal Feature Extraction and Potential Game-Based Reinforcement Learning Framework," is 18,000 RMB. This budget will cover essential expenses related to data acquisition, model development, experimentation, and dissemination activities.

Individual project estimated budget table

Category	***Budget (RMB)***
Computational Resources and Equipment	6,000
- High-performance computing (HPC) resources and cloud services	*4,000*
- Software licenses for reinforcement learning frameworks	*1,500*
- Data storage and processing platforms	*500*
Data Acquisition and Preprocessing	4,000
- Acquisition of spatio-temporal population flow data	*2,000*
Total	18,000

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Individual project estimated budget table (Continued)

Category	***Budget (RMB)***
- Data preprocessing services and tools	*2,000*
Model Development and Experimentation	6,000
- Development and optimization of reinforcement learning algorithms	*3,000*
- Experimentation and validation on real-world datasets	*2,500*
Project Dissemination and Presentation	2,000
- Conference and workshop travel expenses	*1,500*
- Printing and materials for project presentation	*500*
Miscellaneous Expenses	1,000
- Contingency fund	*700*
- Communication and internet services	*300*
Total	18,000

2.4.2 Budget Breakdown

The budget allocation for my individual project, ”Collaborative Public Resource Allocation: A Spatio-temporal Feature Extraction and Potential Game-Based Reinforcement Learning Framework,” is categorized as follows:

1. **Computational Resources and Equipment (33% of Budget)**: 6,000 RMB allocated for high-performance computing (HPC) resources, cloud services, and software licenses for reinforcement learning frameworks necessary for data processing and model development.
2. **Data Acquisition and Preprocessing (22% of Budget)**: 4,000 RMB for acquiring and preprocessing spatio-temporal population flow data, as well as ensuring data compatibility with the model and integration into the broader system.
3. **Model Development and Experimentation (33% of Budget)**: 6,000 RMB to support the development, optimization, and validation of the reinforcement

learning model, as well as for experimentation with real-world datasets and performance evaluation.

4. **Project Dissemination and Presentation (11% of Budget)**: 2,000 RMB for conference travel, poster printing, and other dissemination activities to present the project's results and findings to the academic community and industry professionals.

5. **Miscellaneous Expenses (1% of Budget)**: 500 RMB for unforeseen expenses, including communication and internet services to support ongoing project collaboration and coordination.

2.4.3 Cost-Effectiveness

This budget is designed with a strong focus on cost-effectiveness, ensuring that each RMB is allocated strategically to achieve optimal outcomes. The following factors guide the allocation and emphasize the efficient use of resources:

1. **Prioritizing Data Quality and Integration**: Ensuring the quality and integration of data is critical for the success of this project, as accurate predictions and effective resource allocation rely on high-quality, synchronized datasets. A significant portion of the budget is dedicated to acquiring and preprocessing spatio-temporal population flow data. This enables the construction of a robust dataset for training and testing the reinforcement learning model, ensuring the effectiveness and reliability of the results.

2. **Investment in Computational Resources**: High-performance computing (HPC) resources, cloud services, and software licenses are essential for model development and data processing. These resources allow the use of advanced reinforcement learning algorithms and spatio-temporal embeddings, which are core to the model's success. The allocation of funds to computational resources enhances the efficiency of the project, enabling faster experimentation and optimization of the model.

3. **Efficient Dissemination and Presentation**: The dissemination of project results is essential to ensure the research reaches relevant academic, professional, and industrial audiences. The budget includes costs for attending conferences, printing posters, and other dissemination activities. These efforts will promote

the findings, foster collaboration with external partners, and support future applications of the model in real-world urban environments.

Through careful planning and strategic allocation of funds, this budget maximizes the potential impact of the project while ensuring the efficient use of resources at every stage of development, from data acquisition to model deployment and dissemination.

2.5 Risk Analysis and Mitigation

2.5.1 Potential Risks or Challenges

The project presents several potential risks and challenges that may impact its development and implementation:

1. **Complexity in Multi-Agent Coordination**: Modeling and optimizing the interactions among multiple agents in a collaborative environment introduces significant complexity. Ensuring convergence to globally optimal solutions while maintaining computational efficiency is a key challenge.
2. **Dynamic Spatio-Temporal Modeling**: Capturing the dynamic spatio-temporal characteristics of population flows using neural network architectures is inherently difficult. Any inaccuracies in the feature extraction process could negatively affect the reinforcement learning framework's performance.
3. **Scalability and Generalization**: Adapting the proposed framework to diverse urban environments with varying population densities and resource characteristics poses challenges. Ensuring that the model generalizes well across different datasets and real-world scenarios requires extensive validation.
4. **Algorithmic Complexity and Resource Requirements**: The integration of potential game theory, reinforcement learning, and spatio-temporal embeddings involves complex algorithms that may demand substantial computational resources. Managing these requirements efficiently is critical to the project's success.

2.5.2 Impact of the Risks

The potential impact of the identified risks includes:

1. **Complexity in Multi-Agent Coordination**: Difficulties in achieving efficient coordination among multiple agents may result in suboptimal resource allocation, reducing the overall effectiveness of the proposed framework.

2. **Dynamic Spatio-Temporal Modeling**: Inadequate modeling of spatio-temporal dynamics could lead to inaccurate predictions of population flows, ultimately impacting the decision-making process and the quality of resource scheduling.
3. **Scalability and Generalization**: Challenges in scaling the framework to diverse urban environments may limit its applicability to specific scenarios, reducing its potential impact across varied smart city contexts.
4. **Algorithmic Complexity and Resource Requirements**: High computational demands could increase the cost and time required for experimentation and deployment, potentially delaying project milestones and reducing accessibility for practical implementation.

To mitigate these risks, the project incorporates several strategies:

1. **Enhanced Algorithmic Design**: Regular optimization and validation of algorithms will ensure computational efficiency and reliable convergence to globally optimal solutions.
2. **Improved Spatio-Temporal Feature Extraction**: By experimenting with various neural network architectures, the framework will identify the most effective methods for capturing dynamic spatio-temporal patterns, reducing inaccuracies.
3. **Extensive Validation Across Diverse Scenarios**: Rigorous testing and validation on multiple datasets and environments will ensure the framework's scalability and adaptability to real-world conditions.
4. **Efficient Resource Management**: Computational requirements will be carefully managed through the use of parallel computing, model compression techniques, and optimized training pipelines.

By addressing these risks proactively, the project ensures the development of a robust, scalable, and effective framework for collaborative public resource allocation in smart cities.

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