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Intelligent Mobility and Executive Logistics: Developing A Predictive Framework for Real-Time Travel Risk and Resource Optimization

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Abstract- Increasing complexity and unpredictability of the transportation environment call for an intelligent approach to executive logistics. Traditional methods of executive travel management usually involve scheduled travel, established travel patterns, and predetermined routes and reactively respond to any disturbances. This study proposes an abstract predictive model of applying intelligent mobility solutions in executive logistics, especially focusing on travel-risk assessment and resource optimization. Based on existing literature reviews on artificial intelligence, machine learning, IoT technologies, GPS-based mobility analytics, travel-time prediction, dynamic routing, and predictive logistics in general, the paper reviews ways how such technologies could be used in order to make proactive decisions in mobility. The proposed model involves real-time data gathering, predictive analysis, travel-risk assessment, travel-time forecasting, dynamic re-routing, and resource allocation, forming a continuous decision-making loop. The proposed decision-making process allows for making transportation decisions considering not only expected travel time but also its reliability, travel risks, schedule of executives, vehicle availability, etc. This paper posits that leveraging these competencies may enable a shift from an otherwise reactive transportation function to become a proactive and adaptive organizational capability. This approach could be applied in various domains, including executive corporate transportation, fleet management, time-sensitive mobility planning, and logistics operations involving highly reliable operations. In conclusion, the research demonstrates that the fusion of artificial intelligence, mobility data, and optimization is capable of establishing the basis for a new generation of executive mobility systems.

Keywords: intelligent mobility; executive logistics; predictive analytics; travel-risk prediction; artificial intelligence; dynamic routing; resource optimization; real-time mobility data; travel-time forecasting.

I. INTRODUCTION TO INTELLIGENT MOBILITY AND EXECUTIVE LOGISTICS

The rapid transformation of transportation and logistics through artificial intelligence (AI), Internet of Things (IoT) technologies, machine learning, global positioning systems (GPS), and real-time data analytics is fundamentally changing how mobility is planned and managed. Transportation systems that once depended heavily on static schedules, historical travel patterns, human judgment, and predetermined routes are increasingly being replaced or complemented by intelligent systems capable of interpreting changing conditions and generating adaptive decisions. This transition is particularly important in executive logistics, where transportation is not merely a matter of moving an individual from one location to another but involves coordinating time, security, reliability, vehicles, personnel, routes, schedules, and other resources simultaneously.

Intelligent mobility is the name for an emerging paradigm in the realm of transportation that involves the use of digital technologies for improving transportation processes, such as movement, accessibility, efficiency, safety, and decision making. Intelligent mobility systems gather data from different sources, analyze this data through different analytical or computational models, and then transform this information into decisions on routes, scheduling, vehicle allocation, and movement conditions. In the field of logistics, this has led to the appearance of Logistics 4.0 – more connected, automated, information-exchanging, and decision-making logistics systems. Chen et al. (2021) prove the value of IoT infrastructure for traffic data in predicting the travel time of freight. Executive logistics refers to a specific implementation of these concepts. High-level executives, government officials, investors, and other individuals are often in situations when even small changes can have important ramifications. A missed meeting, delayed airport transfer, unexpected road closure, vehicle breakdown, severe traffic congestion, or exposure to an unsafe travel environment can affect business operations, organizational commitments, and strategic decision-making.

As a result, the issue of executive mobility cannot be dealt with through regular route planning. Predictive intelligence has to answer the following questions:

What is the optimal route? How much will it take to cover the distance? What new risks appear on the way? What route gives a good compromise between the fastest route and the most secure one? Is there a need to allocate another vehicle? To switch drivers? To change the time of departure? What kind of response measures should be taken in case of deteriorated conditions?

The listed questions highlight the necessity for predictive intelligence in executive logistics.

In general, the traditional transportation planning process starts from the known information about a situation and builds the optimal path based on that. But the reality is that any transport environment is dynamic in nature: traffic conditions change, accidents occur on roads, weather changes, vehicle condition changes, etc. Thus, what is optimal at 8:00 can become highly inefficient or risky by 8:30. This means that the executive logistics system based only on initial information will quickly become obsolete.

Fleischmann et al. (2004) established an important foundation for this argument through their work on dynamic vehicle routing based on online traffic information. Their research demonstrates how transportation decisions can be modified as new traffic information becomes available rather than treating routing as a completely static process. Similarly, Kim et al. (2005) examined vehicle-routing decisions under real-time traffic information, demonstrating the value of incorporating changing traffic conditions into routing decisions.

Real-time information is even more important due to the emergence of large mobility datasets in the digital age. GPS trajectories, vehicle sensors, traffic camera data, road monitoring technologies, weather information, and transportation infrastructure that are interconnected can provide real-time information about transportation environments. This information may be useful in creating a continuously updated travel environment profile.

Thus, for example, Sihag et al. (2022) investigated machine learning techniques for prediction of travel time based on GPS trajectories in heterogeneous traffic situations. This research demonstrates how the data related to movement can be used not only for retrospective purposes but also for prediction.

There are significant consequences for executive logistics. Rather than obtaining just an estimated time of arrival, the executive will obtain a smart mobility assessment based on a predicted travel time, reliability of the route, potential traffic risks, alternative routes, and available resources. Thus, the focus should be shifted from navigation to mobility management.

This distinction plays an essential role in the current research. Conventional navigation systems mostly provide the answer to the question: "Where should the traveler go?" Predictive Executive Logistics Framework tries to provide an answer to a wider question: "How can the movement be accomplished in the safest, most reliable, and effective way?"

Such framework would involve using several types of intelligence. Firstly, situational intelligence to understand the current transport situation. Secondly, predictive intelligence to understand the future transport situation. Thirdly, decision intelligence to make the right decisions regarding that situation. Fourthly, optimization intelligence to use the available means of transport, drivers, time, fuel, and any other resources effectively.

It becomes clear that such an approach is important because of the recent changes in the field of logistics performance measurement. As shown by the example of the Logistics Performance Index 2.0 developed by the World Bank, the focus on shipment-level and large-scale data increases (World Bank, 2025). This development demonstrates that logistics systems increasingly depend on the ability to collect, interpret, and act upon granular transportation data.

Within executive mobility, the same principle can be applied at the individual journey level. Every journey can generate data concerning departure time, route, travel speed, delays, stops, traffic conditions, vehicle performance, and arrival reliability. When accumulated over time, these data can form a valuable knowledge base for predictive planning.

This research therefore defines the concept of executive logistics as a dynamic decision-making environment rather than a mere transportation issue. The executive will not just be a passenger; rather, he/she will travel in an operationally-scheduled journey. Transportation will influence the meetings, engagements, organizational activities, security aspects, use of resources, and executive productivity.

Therefore, an intelligent mobility approach can offer benefits in three levels that are related to each other. These include: an operational level, where an effective route choice, scheduling, vehicle utilization, and travel time efficiency can be ensured; a risk management level, where emerging risks can be identified to take preventative measures; and a strategic level, where aggregated intelligence regarding mobility will help the organization understand transportation trends, resource needs, disruption issues, and areas of potential improvements.

It is therefore argued in this research that executive logistics can be significantly enhanced through a transition from reactive transportation management to proactive mobility management.

II. THE EVOLVING ROLE OF PREDICTIVE INTELLIGENCE IN EXECUTIVE TRAVEL MANAGEMENT

Predictive intelligence refers broadly to the use of historical and real-time information, statistical techniques, machine-learning models, and other computational approaches to anticipate future conditions and support decisions before events occur. In transportation and logistics, predictive intelligence can be applied to travel time, congestion, traffic risk, vehicle demand, disruptions, route reliability, and resource requirements.

Its importance arises from the uncertainty inherent in mobility systems. Executives typically operate according to schedules established in advance, while the transportation environment continuously changes. This creates a fundamental mismatch between fixed schedules and dynamic travel conditions. Predictive intelligence provides a mechanism for reducing this mismatch.

Travel-time prediction is perhaps one of the most advanced applications. In Chen et al. (2021), we see an example of how traffic IoT solutions and big data analytics can predict freight travel times. The research shows us how transportation data can advance logistics scheduling beyond simplistic historical averages.

In another example, Servos et al. (2020) look at using machine learning for predicting travel time in multimodal freight transportation. The research is especially relevant to executive logistics as it shows the potential of machine learning for predicting the outcome of transport when several factors affect the journey duration.

The ability to predict thus allows turning the static timetable of an executive's journey into the probability-based schedule. Rather than saying that the journey will last exactly 45 minutes, an intelligent system can evaluate the probability that the journey will be longer than a particular threshold based on current conditions. The point is that executives are usually more interested in reliability than in optimistic travel times on average.

For example, if two routes have predicted travel times of 40 and 45 minutes respectively, a conventional system might recommend the first route. However, if the first route has a high probability of severe congestion while the second has considerably greater reliability, an intelligent executive logistics system may recommend the second route. The decision is therefore based not simply on expected travel time but on risk-adjusted travel performance.

Predictive intelligence will also enhance the early-warning mechanism. The system will realize the occurrence of congestion in the executive’s route and assess its impact on their time of arrival even before the problem becomes serious. In turn, the executive logistics team can adjust their time of departure, find another route, employ another vehicle, or reschedule.

The above-mentioned proactive approach is in line with the studies conducted on traffic risk prediction in real-time conditions. Wu et al. (2025) have proposed the traffic-risk prediction framework with cost-sensitive learning and dynamic thresholds. The importance of the proposed approach is in the ability to assess risks continuously instead of assessing them as the inherent features of a particular road or trip.

As the field is advancing, more advanced technologies are being used. For instance, according to Cheng et al. (2026), the framework based on spatiotemporal hybrid deep learning was proposed to forecast freeway crash-risk levels in real-time conditions.

For executive travel management, the practical implication is the creation of a predictive travel-risk profile for each journey. Such a profile could combine variables such as:

- current traffic conditions;
- predicted congestion;
- historical route reliability;
- reported incidents;
- road conditions;
- weather conditions;
- expected travel time;
- vehicle availability;
- driver availability; and
- proximity to alternative routes.

The resulting risk profile would allow the executive logistics team to distinguish between journeys that are merely delayed and journeys that require strategic intervention.

Another important dimension of predictive intelligence is resource forecasting. Executive logistics involves limited resources. An organization may have a finite number of vehicles, professional drivers, security personnel, fuel capacity, parking arrangements, and scheduling windows. Predictive systems can estimate future resource requirements based on expected movements.

This principle connects executive mobility with broader supply-chain risk management. Aljohani (2023) discusses the application of predictive analytics and machine learning to real-time supply-chain risk mitigation and agility. Although the study operates at the broader supply-chain level, its underlying principle is applicable to executive logistics: organizations can use predictive information to identify emerging risks and adjust resources before disruptions become operationally significant.

Hussein and Ali (2025) similarly examine machine-learning-driven predictive analytics for real-time supply-chain risk management, including anomaly detection, forecasting, dynamic planning, and resource allocation. These capabilities are directly relevant to an executive mobility environment where resource requirements may change rapidly in response to traffic, scheduling, or operational disruptions.

Predictive intelligence also enables continuous learning. Every completed journey produces additional data. The system can compare predicted travel times with actual travel times, evaluate whether its risk predictions were accurate, identify recurring disruptions, and refine future recommendations. Over time, this creates an adaptive system in which the quality of recommendations improves as more operational data become available.

This creates an important feedback loop:

Journey Data → Prediction → Decision → Journey Outcome → Performance Evaluation → Model Improvement

Such a feedback mechanism distinguishes an intelligent logistics system from a conventional scheduling platform. The latter may store journey records, while the former uses those records to improve subsequent decisions.

The evolution toward intelligent executive travel management can therefore be understood as a progression through four stages:

Reactive management responds after disruptions occur.

Descriptive management identifies what happened.

Predictive management estimates what is likely to happen.

Prescriptive management determines what should be done in response.

The proposed research moves executive logistics toward the final two stages. Predictive intelligence should not merely produce forecasts; it should convert forecasts into actionable recommendations.

This is particularly important because the value of prediction is limited if decision-makers cannot act on it. A prediction that congestion will increase in 20 minutes is useful only if the organization can respond by changing routes, adjusting departure times, reallocating vehicles, or modifying the executive's schedule.

Consequently, predictive executive logistics should be understood as an integrated forecast-to-action system. Its purpose is not simply to improve the accuracy of travel predictions but to improve the quality, reliability, safety, and efficiency of executive mobility decisions.

The combination of predictive travel-time estimation, real-time risk assessment, dynamic routing, and resource optimization therefore establishes the conceptual foundation for the predictive framework proposed in this research.

III. REAL-TIME TRAVEL RISK IDENTIFICATION AND PREDICTION

Travel risk within executive logistics extends beyond the possibility of accidents. It encompasses any condition capable of disrupting, delaying, or compromising the reliability and safety of an executive journey. Traffic congestion, road incidents, adverse weather, infrastructure failures, unexpected delays, vehicle problems, and unpredictable changes in transportation conditions can all affect executive mobility. Consequently, an effective intelligent mobility system must be capable of identifying risk as it emerges and estimating how that risk may influence the planned journey.

The conventional method for travel planning assumes that the concept of risk is relatively static. For instance, a route may be safe if it has always been stable with respect to disruptions while another one may not be a good choice because of existing congestion or accidents. The problem is that such a traditional classification system cannot account for fast changes in the state of transportation systems. A normally reliable road can suddenly become not fit for use due to an accident, traffic congestion, weather conditions or any other unforeseen circumstances. That is where real-time risk prediction comes to help.

In their article "A Cost-Sensitive Dynamic Threshold Real-Time Traffic-Risk Prediction Framework" (2025), Wu et al. prove how valuable such an approach may be. It is very important to notice that prediction mistakes have different consequences depending on the context of a particular application area. For example, making a mistake when predicting travel risks may have rather serious consequences. This principle is particularly relevant to executive logistics, where the objective should not simply be to maximize prediction accuracy but to prioritize potentially consequential risks.

It is possible to have a predictive executive mobility system that will be able to determine the risk score associated with a trip. The score may vary according to new information acquired about the trip. As such, a certain route may be classified as low risk during the initial assessment but later be considered high-risk after the identification of congestion on the same road or after an accident has occurred. The executive logistics staff will thus receive a revised recommendation rather than the initial one.

Further evidence of this can be found in the recent development of deep learning models that are capable of assessing risk dynamically. Cheng et al. (2026) proposed a hybrid spatiotemporal deep-learning model for predicting real-time crash risk on freeways. In their study, the importance of understanding transportation risks from spatiotemporal characteristics is clearly brought out. Spatial characteristics refer to the location of the risk. On the other hand, temporal characteristics refer to the risk variation in time. This is particularly important for executive mobility as one route can vary greatly depending on when it is being traversed.

The use of spatiotemporal modelling suggests that executive travel risk should not be represented simply as a characteristic of a destination or road. Instead, risk should be treated as a time-dependent property of a journey.

For example, Route A may have historically low risk between 10:00 a.m. and 11:00 a.m. but significantly greater congestion between 7:30 a.m. and 9:00 a.m. A predictive system can identify this variation and incorporate it into travel planning. Similarly, a road may become increasingly risky when traffic density exceeds a particular threshold. The system can therefore monitor changes in transportation conditions and adjust its prediction accordingly.

Vehicle trajectory data provide another valuable source of risk intelligence. Research on real-time risky-road detection has demonstrated that movement patterns obtained from vehicle trajectories can be used to identify locations associated with elevated risk. Large-scale GPS records can reveal unusual vehicle behaviour, unstable traffic patterns, or road segments where movement conditions differ substantially from normal patterns. This creates the possibility of using aggregated mobility data to identify risk even before conventional incident reports become available.

The integration of trajectory information into executive logistics can produce a more granular understanding of travel conditions. Instead of evaluating an entire journey as either "safe" or "unsafe," the system can divide the journey into segments and assign different risk levels to each segment. This enables more precise intervention.

A journey could therefore be represented as:

Origin → Low-Risk Segment → Moderate-Risk Segment → High-Risk Segment → Destination

If the high-risk segment can be avoided through an alternative route, the system can recommend a route change. If no suitable alternative exists, it can recommend an earlier departure, a different vehicle, or another operational response.

The identification of risk should also incorporate uncertainty. Predictive models rarely possess complete information about future transportation conditions. Consequently, a robust executive logistics system should distinguish between a highly certain prediction and a prediction associated with considerable uncertainty.

For instance, a system may predict that a journey will take 45 minutes with relatively high confidence. Alternatively, it may predict a travel time of 40–60 minutes because traffic conditions are unstable. The second scenario should be treated differently because the range of possible outcomes creates greater scheduling risk.

This leads to the concept of risk-adjusted travel planning. Rather than optimizing solely for the shortest expected travel time, the system should balance travel duration against reliability and risk. This approach is particularly important for executive appointments where arriving late may have greater consequences than spending an additional few minutes travelling.

The same principle applies to route selection. A route with a predicted travel time of 35 minutes but a high probability of significant delay may be inferior to a route with an expected travel time of 42 minutes but much greater reliability. Therefore, the framework proposed in this research should evaluate routes according to multiple dimensions rather than a single travel-time variable.

These dimensions may include:

- predicted travel time;
- travel-time variability;
- traffic congestion;
- incident probability;
- road-condition risk;
- weather-related risk;
- route reliability;
- vehicle availability; and
- resource implications.

The resulting decision can be expressed conceptually as a risk-adjusted mobility utility, where the preferred route is not necessarily the shortest route but the route that produces the best overall operational outcome.

The importance of this approach is supported by research into reliable vehicle routing. Almutairi and Owais (2025) examined vehicle routing using traffic-sensor information and stochastic traffic conditions. Their work illustrates how routing decisions can account for uncertainty rather than assuming that transportation conditions remain deterministic.

This is particularly valuable for executive logistics because uncertainty is itself a source of operational risk. A journey that is consistently predictable may be preferable to a theoretically faster journey characterized by substantial variability.

Real-time risk identification can also support early intervention. If a system detects that the probability of a disruption is increasing, it can generate alerts before the disruption materially affects the journey. Depending on organizational policy, the system could recommend:

1. maintaining the existing route;
2. changing the route;
3. departing earlier;
4. delaying departure;
5. assigning an alternative vehicle;
6. adjusting the executive's schedule; or
7. activating additional logistical resources.

The important point is that risk prediction becomes valuable when it is connected to a decision mechanism.

Executive logistics can consequently benefit from a hierarchical risk system. At the first level, the system monitors raw mobility conditions. At the second level, it converts those conditions into risk indicators. At the third level, it predicts the likely effect of the risk on the journey. At the fourth level, it recommends an appropriate response.

This can be conceptualized as:

Mobility Data → Risk Detection → Risk Prediction → Impact Assessment → Executive Decision

Such a structure provides a stronger basis for proactive mobility management than conventional navigation.

Another factor that is significant is that of travel risk being cumulative in nature. Separate factors may be of negligible risk, but when taken into account together, they can present a considerable risk. Moderate congestion, adverse weather conditions, insufficient vehicle availability, and a packed schedule for an executive are some examples that may collectively represent a significant risk even if there is no individual risk.

In such a scenario, an intelligent system would need to consider all risk factors holistically. This can be done using machine learning tools because machine learning tools can help in the identification of relationships between multiple variables. Aljohani (2023) highlights the significance of machine learning in risk assessment and prediction in order to enable real-time supply chain agility. This same principle can be extended to mobility environments where different interacting variables affect transportation.

Moreover, the system can set up risk thresholds depending upon the importance of the particular journey. All journeys by executives do not have the same level of requirements. For example, an internal meeting can afford to have a greater probability of delay than an airport drop-off, an international business meeting, or a corporate event.

Therefore, executive mobility prediction should be context-sensitive. The system should consider not only the characteristics of the route but also the importance and timing of the executive's destination.

This produces a more sophisticated decision model in which the same transportation conditions may result in different recommendations depending on the operational context.

IV. INTELLIGENT TRAVEL-TIME FORECASTING AND ROUTE ADAPTATION

Travel-time forecasting represents another fundamental component of intelligent executive logistics. The ability to estimate when an executive will arrive is essential for coordinating meetings, appointments, transfers, vehicle schedules, security arrangements, and other activities. However, accurate forecasting requires more than calculating the distance between two locations and dividing it by an assumed average speed.

Transportation systems are dynamic systems, where travel time can be influenced by various interacting parameters. Travel time can change based on the amount of traffic, road capacity, incidents, weather, driving behavior, time of day, traffic lights, construction, and sudden disturbances. Thus, travel-time prediction should have the capability to consider varying influences.

The importance of machine learning in such circumstances is highlighted by Sihag et al. (2022), as in their study on predicting travel time by using GPS trajectories with heterogeneous and chaotic traffic. The researchers illustrate how past movements can be turned into predictions and not remain just the data for analysis.

GPS trajectory data is especially useful since they represent information about the actual movement and not just planned routes. By collecting a significant amount of GPS data, one can get information about average speeds, congestion patterns, specific delays for each route, and differences between different times of the day.

Servos et al. (2020) similarly demonstrate the application of machine-learning algorithms to travel-time prediction in multimodal freight transport. Although their focus is freight transportation, the underlying concept has direct relevance to executive mobility: travel-time forecasting can incorporate multiple variables and transportation conditions rather than relying exclusively on fixed assumptions.

A predictive executive logistics system should therefore generate a dynamic estimated time of arrival (ETA). Unlike a static ETA calculated at the beginning of a journey, a dynamic ETA is recalculated continuously as new information becomes available.

For example, an executive may begin a journey with an estimated arrival time of 9:40 a.m. If congestion increases along the route, the system may revise the estimate to 9:48 a.m. It may simultaneously identify an alternative route that could restore the arrival time to 9:41 a.m. The system can then recommend the alternative based on the trade-off between time, risk, and resource requirements.

This illustrates the connection between forecasting and route adaptation.

Travel-time prediction without route adaptation provides information but does not necessarily improve the journey. Conversely, route adaptation without reliable forecasting may result in unnecessary or poorly informed changes. The two functions therefore need to operate together.

Dynamic vehicle-routing research provides an important theoretical foundation for this concept. Fleischmann et al. (2004) demonstrated how online traffic information can support dynamic vehicle-routing decisions. Kim et al. (2005) likewise examined vehicle-routing optimization when traffic information changes in real time. Together, these studies establish the principle that transportation decisions should be capable of responding to evolving traffic conditions.

In executive logistics, this principle can be extended beyond ordinary vehicle routing. The system may consider not only which route a vehicle should follow but also whether the journey should begin at all, whether departure should be delayed or advanced, whether a different vehicle should be assigned, and whether the executive's schedule should be adjusted.

Route adaptation should therefore be viewed as a continuous optimization process rather than a single decision made before departure.

A useful conceptual sequence is:

Initial Route → Real-Time Monitoring → Updated Forecast → Risk Evaluation → Alternative Route Assessment → Route Adjustment → Continued Monitoring

The process repeats until the executive reaches the destination.

The importance of continuous adaptations becomes evident when the transportation system experiences rapid changes in its environment. A route which is optimal at the time of departure will not remain optimal after 15 minutes. An offline approach can only adapt to such circumstances if it gets linked to real-time information.

Another study by Bertsimas et al. (2019) strengthens the case for scalability of online vehicle routing methods. The research paper discusses the use of online vehicle routing in cases where there is a need to make decisions regarding routing in large-scale transportation systems that are continuously evolving.

However, route adaptation should not automatically mean selecting the fastest available route. Executive mobility requires a broader optimization objective. A route can be evaluated according to:

Route Value = Travel Efficiency + Reliability + Safety + Resource Efficiency

This multidimensional approach reflects the distinctive requirements of executive logistics.

For instance, a route that reduces travel time by five minutes but substantially increases uncertainty may not be preferable. Similarly, a route that is slightly longer but provides greater reliability may produce a better overall operational outcome.

Traffic sensors can improve this decision process. Almutairi and Owais (2025) demonstrate the value of integrating traffic-sensor information into reliable vehicle-routing problems. Sensor-based information can provide real-time or near-real-time indicators of traffic flow and road conditions, allowing routing models to respond to transportation changes.

IoT infrastructure provides another layer of intelligence. Chen et al. (2021) illustrate how traffic-related IoT infrastructure can support predictive freight travel-time management. In an executive logistics environment, similar infrastructure can connect vehicles, traffic systems, GPS devices, organizational scheduling platforms, and mobility-management systems.

This connectivity creates the possibility of a real-time mobility control environment.

The executive logistics team could therefore monitor a dashboard containing:

- current executive location;
- predicted arrival time;
- current route;
- alternative routes;
- route risk scores;
- traffic conditions;
- vehicle status;
- driver availability;
- scheduled commitments; and
- recommended actions.

Such a system transforms transportation management from a largely manual coordination function into a data-driven decision-support function.

Another important capability is multi-route comparison. Rather than presenting one recommended route, an intelligent system can evaluate several alternatives simultaneously. Each route can receive a composite score based on travel time, reliability, risk, distance, fuel requirements, and resource availability.

Suppose three routes are available:

- Route A: shortest travel time but high congestion risk;
- Route B: moderate travel time and low risk;
- Route C: longest travel time but extremely high reliability.

The optimal decision depends on the executive's schedule and the cost of delay. A system that understands these contextual variables can select the route that best satisfies the actual operational objective.

This represents a shift from shortest-path navigation to context-aware mobility optimization.

This same approach can be applied to multimodal travel. In case traffic gets heavy enough, a smart system could assess whether using another form of transportation would be a more reliable option, considering the situation and available options at hand of the executive. Servos et al. (2020) present the significance of multimodal travel-time prediction in terms of transportation logistics.

Intelligent travel-time forecasting and route adaptation thus serve as the connection between prediction and taking action. First, the system makes an assessment of the likely future events, then considers their implications, compares options, and consistently adjusts the travel plan.

In the case of executive logistics, this functionality allows improving punctuality, avoiding unnecessary delays, making better use of vehicles and providing decision makers with better control over current trips. This is crucial because it provides the basis for the next element of the framework, that is, resource optimization based on predictions of mobility conditions.

V. RESOURCE OPTIMIZATION IN EXECUTIVE LOGISTICS OPERATIONS

Resource optimization is a central component of executive logistics because mobility decisions are made within conditions of limited time, vehicles, personnel, fuel, and financial resources. An organization may have several executives requiring transportation simultaneously, a limited fleet of vehicles, a finite number of professional drivers, and overlapping schedules. Consequently, effective executive logistics requires more than identifying the best route; it requires determining how available resources should be allocated to achieve reliable and efficient movement.

Classical resource allocation typically relies on pre-planning. Vehicles and drivers are allocated based on expected journeys, and any changes are manually done in case of disturbances. However, this strategy may become ineffective in case traffic situation, journey duration or schedule of the executives are unexpectedly altered. Predictive logistics offers possibilities for continuous reallocation of resources based on the expected needs.

The idea of dynamic resource allocation is closely related to advances in the field of vehicle routing. For instance, Bertsimas et al. (2019) prove that the online vehicle-routing strategies may be successfully applied for making large-scale transportation decisions using newly available information. At the same time, Fleischmann et al. (2004) illustrate that vehicle routes can be dynamically changed using the information about traffic condition. This idea can be extended to executive transportation by means of changing the current allocation of vehicles and drivers in case predicted situations become unfavorable for the current allocation.

For instance, in case of predicted traffic congestion during an executive's journey, the system could identify whether it is possible to use another vehicle or driver. If several executives have overlapping schedules, the system could evaluate which vehicle allocation minimizes total travel time while maintaining required service levels.

Resource optimization should therefore consider several variables simultaneously:

- vehicle availability and location;
- driver availability;
- executive schedules;
- predicted travel times;
- route risks;
- fuel consumption;
- distance;
- expected delays; and
- priority of each journey.

This creates a multi-objective optimization problem. The objective is not simply to minimize transportation costs but to achieve an appropriate balance between reliability, safety, time, and resource utilization.

This notion can be exemplified by the stochastic model predictive control for vehicle routing method developed by He et al. (2026). In this case, the system takes into account uncertainties associated with the transportation process and updates its routing decisions on a continuous basis according to new information. The importance of this solution for executive logistics stems from the fact that resource decisions can be changed if there are some uncertainties regarding the transportation process.

The same principle can be used in the context of vehicle scheduling. If a vehicle is expected to perform a certain executive assignment by 10:00 a.m., it might become unavailable due to the unexpected delay in the performance of the previous assignment. In order to prepare for this contingency, a predictive system might suggest whether to reserve another vehicle for this purpose. In this context, the notion of predictive resource buffering can be mentioned.

For instance, if three executives have important appointments within a narrow time window and traffic predictions indicate widespread congestion, the system may recommend assigning additional vehicles before the congestion becomes severe. Such an intervention could prevent cascading delays across the executive schedule.

Resource optimization could also enhance the efficiency of vehicles. Vehicles that are idle for long durations are underused resources, whereas vehicles tasked with a very difficult schedule might be problematic when it comes to reliability. Such an intelligent system would consider the historical and

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future demands in order to optimize the utilization of vehicles.

This principle is congruent with more extensive supply-chain research focused on predictive analytics. According to Aljohani (2023), predictive analytics and machine learning are among the crucial instruments that enable a supply chain to become more flexible and resilient. Forecasting, anomaly detection, dynamic planning, and resource allocation are the same concepts mentioned by Hussein and Ali (2025) as important aspects of logistics management using machine learning technology.

Time is another important resource that needs to be optimized. Time has a strategic importance in executive logistics due to the fact that executives are very busy and follow a very tight schedule. Thus, any delays caused by transportation can cause other appointments to be affected as well.

A route that saves ten minutes may be more valuable for an executive with several subsequent appointments than for someone with a flexible schedule. The optimization system should therefore incorporate the executive's schedule into its decision-making rather than treating transportation as an isolated activity.

This leads to a broader concept of schedule-aware mobility optimization. Under this model, transportation decisions are evaluated according to their effect on the entire executive schedule.

The system could calculate:

Transportation Decision → Expected Arrival → Effect on Next Commitment → Resource Requirement → Overall Schedule Reliability

This approach makes executive logistics more closely connected to organizational operations.

Resource optimization can also extend to fuel and vehicle operating costs. Dynamic routing can reduce unnecessary distance and idling, while predictive scheduling can prevent inefficient vehicle movements. Chen et al. (2021) demonstrate the broader importance of predictive traffic and travel-time information in improving logistics management.

The World Bank's logistics research further emphasizes the increasing importance of connectivity, shipment visibility, and data-driven logistics performance measurement. The movement toward more granular logistics data creates opportunities for organizations to improve the visibility of transportation resources and operational performance (World Bank, 2025).

The proposed framework therefore treats resource optimization as a continuous process rather than a one-time scheduling activity. As travel conditions change, resource requirements change; as resource availability changes, optimal routes and schedules may also change.

VI. INTEGRATION OF AI, IOT, GPS, AND REAL-TIME MOBILITY DATA

The efficiency of logistics management by intelligent executives relies to a large extent on having access to relevant data in real-time. The artificial intelligence offers the ability to analyze, but AI systems need quality data for their predictions. IoT devices like GPS units, traffic sensors, vehicles, weather system, road monitoring technology, schedule systems, and many others can offer relevant data for analyzing the mobility environment.

GPS plays an essential role because it continuously offers information about the current location of the vehicle and how it moves. It helps identify regular travel routes, speeds, delays, and reliability of certain routes. Sihag et al. (2022) highlight the benefits of GPS trajectories in travel-time predictions, and Chen et al. (2021) prove the potential of IoT enabled traffic data for predictive logistics management.

The significance of these data combined together exceeds that of each of them alone. For example, GPS shows the current location of the vehicle, but sensors can reveal why it slows down or speed up. Also, the weather data and scheduling data help better understand the consequences of delays.

An integrated system could therefore process:

GPS + Traffic Sensors + Weather + Road Conditions + Vehicle Data + Executive Schedule + Historical Data

The AI layer would then transform these inputs into predictions and recommendations.

This architecture is consistent with the intelligent transport systems where information from various connected sources is analyzed in order to make transportation decisions. For instance, Almutairi and Owais (2025) show how the information from traffic sensors is used in making reliable routing decisions.

AI is capable of doing a number of operations within the proposed architecture. The machine-learning models would be able to predict the travel time, while classification models would help in determining risk levels. Deep-learning models would detect complex spatial and temporal patterns, while optimization algorithms would find the optimal combination of routing and resource allocation.

Recent research confirms that these operations have become increasingly complex. Cheng et al. (2026) develop a hybrid spatiotemporal deep-learning framework for the real-time crash-risk prediction, thereby showing how AI is capable of processing complex transportation patterns. Similarly, Wu et al. (2025) show how machine learning can be used for dynamic traffic-risk classification.

In that case, the integration of AI and IoT leads to a transformation of connected transportation into intelligent transportation. IoT provides information; AI analyses this information; optimization mechanisms turn this analysis into actions.

For executive logistics, this can produce a centralized mobility intelligence platform. The platform would continuously receive data, evaluate current and future conditions, and present decision recommendations to logistics managers or authorized decision-makers.

A simplified architecture can be represented as:

Data Sources → Data Integration → AI Prediction → Risk Assessment → Optimization → Executive Mobility Decision → Feedback

The feedback component is important because completed journeys generate new data. Actual travel time can be compared with predicted travel time, while predicted risks can be compared with actual events. This allows the system to identify prediction errors and improve future performance.

The integration of these technologies also creates opportunities for organizational learning. Repeated journeys can reveal which routes are consistently reliable, which time periods create the greatest risks, which vehicles experience recurring delays, and how effectively resources are being utilized.

The ultimate value of AI, IoT, and GPS integration therefore lies not in the technologies individually but in their ability to create a continuous decision-support environment for executive logistics.

When these capabilities are combined with predictive travel-risk assessment, dynamic routing, and resource optimization, they provide the technological foundation for the integrated predictive framework discussed in the next section.

VII. DEVELOPING AN INTEGRATED PREDICTIVE FRAMEWORK FOR EXECUTIVE MOBILITY

The preceding sections establish that effective executive mobility requires the integration of travel-risk prediction, travel-time forecasting, dynamic routing, and resource optimization. These capabilities are individually valuable, but their greatest potential emerges when they operate as components of a single decision-support framework. The proposed predictive framework therefore combines real-time mobility data with artificial intelligence, risk assessment, forecasting, and optimization to support proactive executive logistics decisions.

The framework can be conceptualized as a continuous cycle:

Data Collection → Data Integration → Prediction → Risk Assessment → Optimization → Executive Decision → Real-Time Monitoring → Feedback

The first layer is the real-time data acquisition layer. It collects information from GPS devices, traffic sensors, connected vehicles, road-monitoring systems, weather information, historical journey records, and executive schedules. Chen et al. (2021) demonstrate the importance of IoT-based traffic information for predictive logistics management, while Sihag et al.

(2022) establish the value of GPS trajectory data for travel-time prediction.

The second layer is the data integration and intelligence layer. Information from different sources is combined to establish a current representation of the transportation environment. This is necessary because no single data source can adequately describe all factors affecting executive mobility. GPS may indicate vehicle location, but traffic sensors can provide information about congestion, while weather data may explain changes in travel conditions.

The third layer is the predictive analytics layer. Machine-learning and deep-learning models can estimate future travel times, identify emerging congestion, predict traffic risk, and detect patterns associated with potential disruptions. Wu et al. (2025) demonstrate how machine learning and dynamic thresholds can support real-time traffic-risk prediction, while Cheng et al. (2026) demonstrate the potential of spatiotemporal deep learning for real-time crash-risk prediction.

At this stage, the system should generate several outputs rather than a single prediction. These may include:

- predicted travel time;
- estimated arrival time;
- travel-risk score;
- route reliability score;
- disruption probability;
- resource requirement; and
- confidence level of each prediction.

The inclusion of confidence levels is important because predictions are subject to uncertainty. A decision-maker should be able to distinguish between a highly reliable prediction and one based on unstable or incomplete information.

The fourth layer is the risk evaluation and decision-making layer. In this step, forecasted conditions will be evaluated in terms of the requirements for the schedule of the executive. A certain level of traffic congestion may be acceptable for a flexible meeting but unacceptable when the executive is headed to a critical time-sensitive event.

Thus, the suggested framework is supposed to be contextual in nature. Instead of evaluating transportation conditions independently from the schedule of the executive, the system needs to evaluate how those conditions will impact the overall schedule.

The fifth layer is the optimization layer. Having identified all risks and forecasted conditions, the system assesses the range of possible actions. They might include sticking to the current route, choosing a different route, changing departure time, replacing the vehicle, replacing the driver, etc.

There is extensive research on the topic of dynamic vehicle routing which forms the basis for this module. Specifically, Fleischmann et al. (2004) explain how online traffic data may assist in dynamic routing, and Bertsimas et al. (2019) demonstrate how the principles of online vehicle routing may be applied to a large-scale transportation environment. More recently, He et al. (2026) demonstrate the use of stochastic model predictive control for vehicle-routing decisions under uncertainty.

The proposed framework extends these principles by applying them specifically to executive mobility and by combining routing with risk and resource considerations.

A conceptual decision function can therefore be expressed as:

Optimal Executive Mobility Decision = f(Travel Time, Risk, Reliability, Schedule, Vehicle Availability, Resource Cost)

This formulation emphasizes that the best mobility decision is a function of multiple variables.

For example, assume an executive has a 10:00 a.m. meeting. The system predicts that the current route will take 35 minutes under normal conditions but has a high probability of congestion. An alternative route requires 42 minutes but has significantly greater reliability. If the executive departs with sufficient time, the second route may represent the superior decision because it reduces the probability of a consequential delay.

The framework therefore prioritizes outcome reliability rather than minimum travel time alone.

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Another important feature is continuous reoptimization. The initial recommendation should not remain fixed throughout the journey. If new information indicates that the selected route is deteriorating, the system should reassess available alternatives.

This creates a closed-loop architecture:

Predict → Decide → Monitor → Reassess → Adapt

Such continuous adaptation is consistent with the principles of dynamic routing and predictive control discussed by Fleischmann et al. (2004) and He et al. (2026).

The framework can also support scenario-based decision-making. Rather than providing one recommendation, it can present several possible scenarios:

Scenario	Expected Travel Time	Risk	Resource Requirement	Recommended Action
Current route	Moderate	High	Existing vehicle	Consider rerouting
Alternative route	Slightly longer	Low	Existing vehicle	Preferred
Delayed departure	Variable	Moderate	Existing vehicle	Conditional
Alternative vehicle	Moderate	Low	Additional resource	Contingency

This approach enables decision-makers to understand the consequences of different choices rather than simply receiving a single automated instruction.

The framework should include the process of learning as well. After every trip, it will be able to compare predictions and real results. For instance, if the travel time predicted by the model was 40 minutes but the real one is 48 minutes, then this difference is a new piece of information for the learning process. Also, if some risks were not realized during the trip, the model may decide whether some changes are needed for the prediction threshold.

The final result of using this approach is the development of an increasingly adaptive mobility system.

In accordance with this approach, the idea of predictive and intelligent supply chain management also plays an important role. According to Aljohani (2023) and Hussein and Ali (2025), predictive analytics and machine learning as well as dynamic decision making play an important role in logistics agility and risk management.

Therefore, the suggested executive mobility framework is different from the conventional navigation system in three aspects: it is predictive, risk-aware, and resource-aware.

Together, these characteristics allow executive logistics to become a proactive operational capability.

VIII. BENEFITS, CHALLENGES, AND PRACTICAL APPLICATIONS OF INTELLIGENT EXECUTIVE LOGISTICS

The implementation of an intelligent predictive framework can provide significant benefits to organizations that manage executive transportation. The first major benefit is improved travel reliability. By predicting congestion and potential disruptions before they materially affect a journey, logistics managers can take preventive action.

Improved reliability may directly affect the efficiency of executives. Executives usually have to attend several events in various places, and the transport disruptions may lead to cascading scheduling difficulties. The ability of the transportation system to predict disruptions and change the route may help to decrease the chance of a missed engagement.

The second benefit is enhanced utilization of resources. The vehicles and drivers may be assigned depending on forecasted demand and not on scheduled operations. The online routing studies prove that dynamic data can be used to increase transportation resource utilization (Bertsimas et al., 2019). In the case of executives' logistics, it means avoiding vehicle idling and improving fleet utilization.

Finally, improved reliability can facilitate proactive risk management. The logistics manager will get early alerts about deteriorating conditions and avoid disruptions caused by unexpected issues. Machine learning studies prove that the modern technology allows predicting transportation risks (Wu et al., 2025; Cheng et al., 2026).

Fourthly, the framework will enable data-based decision making. Rather than depending entirely on the experience of the driver or manual coordination, the executives and logistics managers will be provided with recommendations that are based on both historical and real-time data. The move by the World Bank towards big-data based logistics performance evaluation points to the larger significance of finer transportation data (World Bank, 2025).

The framework has many potential applications.

It may be used for coordinating the transportation of executives between office, airport, hotel, conferences, and other business appointments. The government and institutional transportation needs can be met through the application. For fleet management of executives, the model can be used to optimize the vehicles and drivers allocated to various executives. It can also be used for airport transfer management where reliability of arrivals is critical since any missed flight would cause significant losses.

High density executive scheduling, where the appointments of several executives overlap, is another area where predictive optimization can help decide on vehicle allocation and resource reservation.

Despite these advantages, implementation presents several challenges.

The first is data quality. Predictive models are dependent on the quality, timeliness, and completeness of the information they receive. Inaccurate GPS data, missing traffic information, outdated road conditions, or unreliable incident reports can reduce prediction quality.

The second challenge is data integration. Different systems may use different formats and standards. Integrating GPS platforms, fleet-management systems, traffic databases, scheduling systems, and weather feeds can require significant technical infrastructure.

The third challenge is model reliability. Machine-learning models can produce incorrect predictions, particularly when they encounter conditions that differ significantly from their training data. Therefore, predictive recommendations should include confidence measures and appropriate human oversight.

The fourth challenge is privacy and governance. Executive mobility data can contain sensitive information about locations, schedules, organizational activities, and movement patterns. Organizations implementing such systems must therefore establish appropriate access controls, data-retention policies, cybersecurity measures, and governance procedures.

A further challenge is the risk of over-automation. Intelligent systems should support decision-makers rather than eliminate human judgment in situations requiring contextual understanding. The most appropriate model is therefore likely to be human-AI collaboration, where AI identifies patterns and generates recommendations while authorized personnel retain responsibility for consequential decisions.

These challenges do not undermine the value of intelligent executive logistics. Instead, they demonstrate the need for careful implementation and governance.

Overall, the combination of predictive analytics, real-time mobility data, dynamic routing, and resource optimization can transform executive transportation from a reactive support function into an intelligent operational capability. The framework's greatest value lies in its ability to connect prediction with intervention: identifying what is likely to happen, understanding its implications, and recommending the most appropriate response before the disruption becomes critical.

IX. FUTURE DIRECTIONS FOR PREDICTIVE AND AUTONOMOUS EXECUTIVE MOBILITY

The development of intelligent executive logistics is likely to move beyond systems that simply predict traffic conditions and recommend alternative routes. Future mobility platforms are expected to become increasingly autonomous, interconnected, context-aware, and capable of coordinating multiple transportation resources simultaneously. The progression from descriptive analytics to predictive and prescriptive intelligence suggests that executive mobility will increasingly depend on systems capable of anticipating disruptions and initiating appropriate responses.

The first key area is related to the creation of advanced multimodal mobility intelligence. Present studies indicate the effectiveness of machine learning in predicting travel time in multimodal freight transport (Servos et al., 2020). Executive logistics platforms of the future may utilize this method and analyze several transportation alternatives at the same time. Instead of assessing other possible roads only, the intelligent system may take into account various combinations of vehicles, departure times, and modes of transportation depending on the specifics of each trip.

Another key trend that is expected to develop further is the increased importance of real-time and high-frequency data. The Logistics Performance Indicators 2.0 of the World Bank demonstrate that shipment-level and large-scale logistics data are becoming increasingly essential in assessing transport performance (World Bank, 2025). With the increase in the spread of connected vehicles, GPS, sensors, and digital infrastructure, there will be even more detailed information on transportation.

This development will improve the granularity of prediction. Instead of predicting travel conditions for an entire city or major road, future systems could estimate conditions at highly specific locations and time intervals. This would enable more precise route adaptation and resource allocation.

Digital twins represent another potential development. A digital twin of an executive mobility operation could create a virtual representation of vehicles, routes, drivers, schedules, and transportation conditions. The system could simulate possible scenarios before recommending an action. For example, it could estimate the consequences of maintaining the current route, changing the route, delaying departure, or assigning another vehicle.

This would transform mobility management from real-time reaction into real-time simulation and decision optimization.

More sophisticated AI will also allow more intricate systems in terms of identifying relationships between various risk factors. The potential of spatiotemporal deep learning for transportation risk prediction is shown by Cheng et al. (2026), whereas the importance of using dynamic thresholds is demonstrated by Wu et al. (2025). The next step can involve incorporating the above into the system with weather conditions, road conditions, vehicle condition, schedules of events, and previous traveling history of the executives.

It may result in creating a personal executive mobility intelligence system. The system will be able to learn the preferences and requirements of different executives without the need to rely solely on transportation models. This system will understand that one of the executives needs punctuality while another does not require it.

One of the possible trends in the future is the autonomous coordination of resources. Instead of informing the logistics manager about the delay of the vehicle, the system will be able to analyze alternative solutions and develop a contingency plan. Depending on organizational permissions, it could reserve another vehicle, notify the assigned driver, update the estimated arrival time, and present the revised plan for approval.

This is consistent with the broader development of online and adaptive vehicle-routing systems. Bertsimas et al. (2019) demonstrate the feasibility of large-scale online vehicle routing, while He et al. (2026) show how predictive control can continuously update routing decisions under uncertainty.

However, greater autonomy will increase the importance of governance and human oversight. Autonomous recommendations must remain explainable, especially when decisions involve safety, significant financial resources, or sensitive executive movements. Future systems should therefore provide not only a recommendation but also the major factors responsible for the recommendation.

For example:

Recommended Route B because Route A has a 34% higher predicted delay probability and an elevated risk score.

Such explanations can improve trust and allow logistics personnel to challenge or override recommendations when additional contextual information is available.

The future of executive mobility will also hinge on increased predictive resilience. Instead of simply optimizing the route under regular operating conditions, systems are going to be developed so that they continue to function when something disrupts the process. The findings of the research on the logistics disruption prediction and mitigation prove this tendency (Zhao et al., 2026).

It is crucial due to the fact that transportation disruptions have a chain effect. If one journey is delayed, it may lead to the delay of the next trip of the same vehicle that will, in its turn, negatively influence the schedule of another executive. This kind of system is able to model dependencies and predict the chain effect.

Therefore, in the future executive logistics systems will not only optimize single trips, but the entire mobility network as well. The proposed framework serves as the basis for such development. It consists of the following key elements: real-time data gathering, predictive risk assessment, travel-time prediction, dynamic routing, and resource optimization.

The ultimate objective should not be to remove human involvement entirely. Instead, the goal should be to create an intelligent partnership in which AI handles large volumes of mobility data and rapidly changing conditions while human decision-makers provide strategic judgment, organizational context, and accountability.

Conclusion

Intelligent mobility represents an important evolution in the management of executive transportation. Conventional logistics systems generally emphasize scheduling, dispatching, and route selection, whereas predictive executive logistics extends these functions by incorporating real-time information, forecasting, risk assessment, and continuous optimization.

As evidenced by the literature discussed in this study, the technological prerequisites to create such a system are present. For example, GPS trajectories may be used for travel-time prediction (Sihag et al., 2022); IoT technology is capable of providing logistics information (Chen et al., 2021); machine learning is applicable to predicting traffic risks (Wu et al., 2025); deep-learning technology is capable of modeling transportation risks (Cheng et al., 2026); and dynamic or stochastic optimization is helpful in making routing decisions (Fleischmann et al., 2004; He et al., 2026).

The primary benefit is the ability to combine the above capabilities within the executive mobility paradigm.

Namely, every executive trip may be considered as an evolving decision-making problem. The real-time data will define the state of transportation environment, while the prediction models will estimate the future transportation environment, and the risk models will identify the possible dangers and disruptions, and the optimization will evaluate the possibilities and alternatives, and the decision-making process will translate these forecasts into mobility decisions.

The resulting architecture can be summarized as:

Real-Time Data → Predictive Intelligence → Risk Assessment → Travel-Time Forecast → Route Optimization → Resource Allocation → Executive Decision → Continuous Feedback

Such a system can improve punctuality, transportation reliability, resource utilization, operational visibility, and proactive risk management. It can also help organizations move from reactive responses to disruptions toward anticipatory mobility planning.

However, for such a vision to come true, reliable data, proper algorithms for AI, good cybersecurity and privacy protection, system integration, and human supervision are all necessary ingredients for success.

Just having good prediction quality is not sufficient – the next step should be made – turning predictions into decision-making process.

The future of executive logistics should lie in the fusion of mobility intelligence and operational intelligence. The transformation of transportation data into predictions, combined with the connection between predictions and the ability to make decisions on allocation of resources, enables executive mobility to become not only a mode of transportation but a strategic capability of an organization with an ability to anticipate and react to uncertain environment.

In this sense, the predictive framework described above creates a theoretical path to the development of the next generation executive logistics systems, which can decide not only about the destination of an executive but about the time, the way, the route, resources and risks to go through this destination.

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