

PREDICTIVE TRAFFIC MANAGEMENT OF INLAND WATERWAYS USING ARTIFICIAL INTELLIGENCE AND SIMULATION MODELS

Abstract. Inland waterway transport is an important part of sustainable freight transportation systems due to its low environmental impact and high transport efficiency. However, increasing traffic density, infrastructure limitations, and operational complexity create significant challenges for navigation management. Modern digital technologies such as Artificial Intelligence (AI), predictive analytics, simulation models, and digital twins provide new opportunities for improving inland waterway traffic management. The aim of this article is to analyse the application of AI and predictive simulation models in inland waterway transport and to evaluate their potential for improving operational efficiency, safety, and sustainability. The article is based on a comparative analysis of scientific literature, simulation approaches, and intelligent transport management systems used in inland navigation. The study focuses on the use of Automatic Identification System (AIS) data, machine learning algorithms, predictive analytics, and simulation techniques for traffic optimization. The results indicate that AI-supported predictive systems can significantly improve traffic flow management, reduce delays, optimize lock scheduling, and minimize fuel consumption. Furthermore, the article proposes a conceptual framework for smart inland waterway traffic management integrating simulation models and real-time operational data. The findings contribute to the development of intelligent transport systems and support the digital transformation of inland navigation.

Keywords: Inland Waterway Transport, Artificial Intelligence, Traffic Simulation, Predictive Analytics, Smart Navigation, Digital Twin, AIS Data, Traffic Management Optimization

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Introduction

Inland waterway transport represents an important component of modern freight transportation systems and sustainable logistics networks. Compared to road transport, inland navigation enables the transportation of large cargo volumes with lower fuel consumption, reduced traffic congestion, and lower environmental impacts. Inland waterways are particularly suitable for transporting bulk commodities, industrial materials, agricultural products, and containerized cargo over medium and long distances. Due to these operational characteristics, inland navigation plays an increasingly important role in multimodal transport systems and integrated logistics chains (T. Notteboom and J.-P. Rodrigue).

The growing emphasis on sustainable transport solutions and environmentally responsible logistics has increased the strategic importance of inland waterway transport in many regions. Inland navigation supports the diversification of freight transport modes and contributes to reducing pressure on overloaded road infrastructure. The integration of inland waterways into regional and international transport corridors improves transport connectivity, strengthens supply chain resilience, and

enhances the efficiency of freight distribution networks (T. Notteboom and J.-P. Rodrigue).

Despite these advantages, inland navigation systems face several operational and infrastructural challenges. One of the most significant problems is the limited capacity of waterway infrastructure, particularly at locks, terminals, and narrow navigation sections. Increasing vessel traffic density may lead to congestion, operational delays, and reduced transport reliability. In addition, inland navigation operations are strongly influenced by environmental and hydrological conditions such as fluctuating water levels, seasonal variations, and weather-related disruptions (P. W. de Langen and K. B. Sharypova).

Another challenge involves aging infrastructure and insufficient modernization of some inland waterway networks. Many transport corridors require significant investments in infrastructure maintenance, modernization of lock systems, and implementation of intelligent traffic management technologies. Traditional traffic management approaches based primarily on static scheduling and manual operational coordination are often unable to respond effectively to rapidly changing traffic conditions and increasing transport demands (P. W. de Langen and K. B. Sharypova).

The rapid development of digital technologies has accelerated the transformation of transport management systems in recent years. Artificial Intelligence (AI), machine learning, predictive analytics, big data processing, and simulation technologies are increasingly integrated into intelligent transport systems in order to improve operational efficiency and support data-driven decision-making (S. Russell and P. Norvig), (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee). These technologies enable the processing and analysis of large operational datasets, identification of traffic patterns, prediction of future operational situations, and optimization of transport processes in real time.

Artificial Intelligence technologies are becoming particularly important in complex transport environments characterized by dynamic operational conditions and large numbers of interacting transport participants. AI-supported systems can analyse historical and real-time operational data simultaneously and continuously adapt operational decisions according to changing traffic conditions. Machine learning methods and predictive analytical models are therefore increasingly applied in traffic forecasting, route optimization, operational planning, and infrastructure management (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee).

One of the most important technologies supporting intelligent inland navigation management is the Automatic Identification System (AIS). AIS is an automated vessel tracking system that provides continuous real-time information about vessel position, speed, heading, navigational status, and vessel identification (International Maritime Organization). AIS technologies significantly improve operational visibility and situational awareness within inland navigation systems.

AIS operational data are widely used for vessel monitoring, traffic flow analysis, congestion detection, route optimization, and predictive transport management. The continuous collection of vessel movement data enables the development of predictive analytical models capable of forecasting traffic situations and identifying potential operational risks (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett). AIS-based predictive systems therefore represent an important component of modern intelligent navigation management systems. Simulation technologies also represent highly important analytical tools in inland navigation research and operational management. Simulation models enable researchers and transport operators to analyse complex operational processes, evaluate infrastructure capacity, identify bottlenecks, and test alternative traffic management strategies without affecting real operational systems (R. M. van der Zee and J. G. A. van der Vorst). Simulation approaches support both strategic planning and operational decision-making in transport management.

Different simulation methodologies are currently applied in inland waterway transport systems. Discrete-event simulation is commonly used for analysing lock operations, vessel scheduling, and terminal logistics, while agent-based simulation focuses on modelling the behavior and interactions of individual vessels and transport

participants (J. Zhang, X. Chen, and L. Li), (R. Boel and L. Mihaylova). More advanced approaches, such as digital twin technologies, integrate real-time operational monitoring with virtual simulation environments and predictive analytical systems (H. Nguyen and T. Kim).

The integration of Artificial Intelligence, AIS operational data, predictive analytics, and simulation technologies creates opportunities for developing intelligent predictive traffic management systems capable of dynamic operational optimization and adaptive decision-making. Such systems can improve traffic coordination, increase infrastructure utilization efficiency, reduce operational delays, and support safer navigation operations.

The aim of this article is to analyse the possibilities of applying Artificial Intelligence and predictive simulation models in inland waterway traffic management. The article focuses on the integration of AIS operational data, predictive analytical methods, and simulation approaches into intelligent inland navigation systems. Particular attention is devoted to the role of predictive traffic management, simulation modelling, and digital transformation in the modernization of inland waterway transport systems.

1. Literature Review: Inland Waterway Transport Systems

Inland waterway transport systems represent an important element of multimodal freight transportation and logistics integration. Inland navigation enables efficient transportation of large cargo volumes and supports the connection between ports, industrial regions, and inland logistics centers (T. Notteboom and J.-P. Rodrigue). Due to relatively low operational costs and high transport capacity, inland waterways are particularly suitable for transporting bulk cargo, industrial products, raw materials, and containerized freight over long distances.

The integration of inland waterways into multimodal transport corridors contributes to improving supply chain efficiency and regional transport connectivity. Modern logistics systems increasingly depend on effective coordination between different transport modes, including road, rail, maritime, and inland waterway transport. Inland navigation therefore plays an important role in reducing transport bottlenecks and improving freight distribution within integrated logistics networks (T. Notteboom and J.-P. Rodrigue).

Efficient inland waterway transport operations require continuous coordination between vessels, locks, terminals, infrastructure operators, and traffic management centers. Operational efficiency strongly depends on infrastructure capacity, vessel scheduling, traffic coordination, and infrastructure reliability. Congestion at locks and terminals may significantly affect transport performance and lead to operational delays across wider transport networks (P. W. de Langen and K. B. Sharypova).

P. W. de Langen and K. B. Sharypova (P. W. de Langen and K. B. Sharypova) emphasize that optimized inland

waterway logistics can substantially improve transport efficiency and operational reliability. Their research highlights the importance of coordinated logistics planning, infrastructure management, and operational optimization in inland waterway systems. Effective traffic management therefore represents a critical requirement for maintaining efficient transport operations under increasing transport demands.

The growing complexity of inland navigation systems creates increasing demands for advanced operational management technologies. Traditional traffic management approaches based on static operational procedures are often insufficient in dynamic operational environments characterized by continuously changing traffic conditions. As a result, intelligent transport management systems capable of real-time monitoring, predictive analysis, and adaptive operational decision-making are becoming increasingly important.

Another important aspect of inland navigation development involves infrastructure modernization and digital transformation. Modern transport systems increasingly integrate digital technologies, operational monitoring systems, and predictive analytical tools in order to improve traffic coordination and infrastructure utilization. The implementation of intelligent management technologies therefore represents an important direction for the future development of inland waterway transport systems.

1.1 Artificial Intelligence in Transport Systems

Artificial Intelligence has become one of the most important technologies in modern intelligent transport systems. AI technologies enable automated processing of large operational datasets, identification of complex traffic patterns, prediction of future operational situations, and support for adaptive decision-making processes (S. Russell and P. Norvig). The increasing availability of operational data and advances in computational technologies have accelerated the implementation of AI methods across different transport sectors.

According to Russell and Norvig (S. Russell and P. Norvig), Artificial Intelligence systems are designed to simulate intelligent behavior through data analysis, learning processes, and autonomous decision-making mechanisms. In transport systems, AI technologies support operational optimization, predictive analysis, and intelligent control processes under dynamic operational conditions.

Machine learning and deep learning methods currently represent some of the most widely applied AI approaches in intelligent transport systems (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee). These methods enable predictive modelling based on historical and real-time operational data. AI-supported analytical systems can identify hidden relationships between operational variables and continuously improve prediction accuracy through adaptive learning processes.

Abduljabbar et al. (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee) state that Artificial Intelligence

applications in transport management include traffic forecasting, route optimization, congestion prediction, infrastructure monitoring, and operational planning. AI systems improve the adaptability of transport management systems and support more effective utilization of transport infrastructure and operational resources.

In inland waterway transport, AI applications are closely connected with AIS operational data analysis. AIS systems continuously generate large volumes of operational data related to vessel movement, navigation behavior, speed, heading, and traffic conditions (International Maritime Organization). These datasets create suitable conditions for applying machine learning models in vessel traffic prediction and operational optimization.

Machine learning approaches using AIS data are especially important for traffic forecasting and predictive operational management. Capobianco et al. (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett) demonstrated that AIS-based machine learning models can effectively predict vessel trajectories and traffic behavior in maritime transport systems. Their findings indicate that AI-supported predictive systems achieve higher forecasting accuracy than conventional statistical approaches.

Artificial Intelligence technologies additionally support operational optimization in inland navigation systems. Predictive analytical models can estimate vessel arrival times, optimize lock scheduling, identify congestion risks, and support adaptive traffic coordination under changing operational conditions. AI systems therefore contribute to improved operational efficiency, reduced delays, and more effective infrastructure utilization.

Another important application area involves navigation safety management. AI-supported monitoring systems can analyse vessel behavior in real time and identify operational anomalies or potentially dangerous navigation situations. Intelligent analytical systems may therefore improve situational awareness and support faster operational responses in critical situations.

The integration of Artificial Intelligence into inland navigation management systems represents an important component of transport digitalization and smart infrastructure development. As inland navigation systems become increasingly data-driven and interconnected, AI technologies are expected to play a central role in future intelligent traffic management systems.

2. Research Methodology

The methodology of this research is based on qualitative analysis and comparative evaluation of scientific studies related to inland waterway transport, Artificial Intelligence applications, predictive analytics, and simulation modelling (R. M. van der Zee and J. G. A. van der Vorst), (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee).

Secondary scientific data were collected from peer-reviewed publications focused on intelligent transport systems, AIS-based traffic prediction, simulation

methodologies, and maritime predictive analytics (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett), (A. Munim and H.-J. Schramm), (J. Zhang, X. Chen, and L. Li).

The research focused on the comparison of traditional traffic management approaches and AI-supported predictive systems. The comparison included several operational criteria such as prediction accuracy, operational flexibility, congestion reduction, and support for decision-making (P. W. de Langen and K. B. Sharypova), (A. Munim and H.-J. Schramm).

Particular attention was paid to simulation approaches including discrete-event simulation, agent-based modelling, and digital twin technologies (R. M. van der Zee and J. G. A. van der Vorst), (R. Boel and L. Mihaylova), (H. Nguyen and T. Kim).

The objective of the methodology was to identify the operational potential of intelligent predictive traffic management systems in inland navigation and to propose a conceptual framework integrating AI technologies, AIS data, and simulation models.

Table 1. Comparison of Traffic Management Methods

Approach	Input Data	Strengths	Limitations	Use in IN
Traditional rule-based control	Static schedules	Simple, low cost	No prediction, rigid	Low
AI-based systems	AIS, historical data	Prediction, adaptability	Data dependency	High
Simulation models	Synthetic + real data	Scenario testing	Computational cost	High
Digital twins	Real-time + simulation	Real-time optimization	High complexity	Very high

3. Artificial Intelligence Applications in Inland Navigation

Artificial Intelligence technologies are increasingly applied in modern transport management systems due to their ability to process large amounts of operational data and support predictive decision-making (S. Russell and P. Norvig), (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee). In inland waterway transport, AI-based systems contribute to improved traffic coordination, operational planning, navigation safety, and transport efficiency.

One of the most significant applications of AI in inland navigation is vessel traffic prediction. Machine learning algorithms can analyse historical and real-time AIS data in order to identify vessel movement patterns and forecast future traffic situations (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett). AIS data provide continuous information about vessel position, speed, heading, and navigational status, which enables the development of predictive traffic models (International Maritime Organization).

Machine learning methods used in intelligent transport systems include regression models, neural networks, and deep learning approaches (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee). These methods can identify complex relationships between operational variables and predicting vessel arrivals, traffic density, and

possible congestion situations. According to Capobianco et al. (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett), AIS-based machine learning models significantly improve traffic prediction accuracy compared to traditional statistical approaches.

Artificial Intelligence also supports operational optimization in inland navigation systems. Predictive analytical models enable transport operators to optimize vessel scheduling, reduce waiting times at locks, and improve traffic coordination (A. Munim and H.-J. Schramm). AI-supported systems can continuously evaluate operational conditions and recommend adaptive traffic management strategies based on real-time data analysis.

Another important application of AI involves navigation safety management. Intelligent monitoring systems can identify abnormal vessel behavior and detect operational anomalies using AIS data analysis (International Maritime Organization), (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee). Such systems improve situational awareness and support faster operational responses in potentially dangerous situations.

The integration of AI technologies into inland navigation additionally contributes to improved transport efficiency. Predictive operational planning enables more effective infrastructure utilization and reduction of operational delays (P. W. de Langen and K. B. Sharypova). As transport systems become increasingly digitalized, AI-based traffic management systems are expected to play a central role in future inland navigation operations (H. Nguyen and T. Kim).

4. Simulation Models in Inland Navigation

Simulation models represent essential analytical tools for studying transport systems and evaluating operational scenarios in inland waterway transport (R. M. van der Zee and J. G. A. van der Vorst). Simulation technologies enable researchers and transport operators to analyse traffic behavior, evaluate infrastructure capacity, and test optimization strategies without interfering with real transport operations.

One of the most used simulation approaches in inland navigation is discrete-event simulation. This method models operational processes as sequences of events occurring over time (R. M. van der Zee and J. G. A. van der Vorst). In inland navigation systems, discrete-event simulation is particularly suitable for analyzing lock operations, vessel scheduling, terminal processes, and infrastructure utilization (J. Zhang, X. Chen, and L. Li). The method allows detailed evaluation of waiting times, congestion situations, and operational bottlenecks.

Zhang et al. (J. Zhang, X. Chen, and L. Li) demonstrated that simulation models can effectively evaluate the traffic capacity of inland waterway networks and identify limitations affecting transport performance. Simulation outputs can support infrastructure planning and optimization of transport operations under varying traffic conditions.

Agent-based simulation represents another important approach in transport system modelling. Unlike aggregate simulation methods, agent-based models focus on the

behavior and interactions of individual transport participants such as vessels, terminals, and infrastructure components (R. Boel and L. Mihaylova). Each agent behaves autonomously according to predefined behavioral rules and reacts dynamically to operational conditions.

According to Smith and Brown (R. Boel and L. Mihaylova), agent-based simulation provides realistic representations of inland navigation systems and enables detailed analysis of vessel interactions and traffic coordination processes. This modelling approach is particularly useful for analyzing complex operational environments characterized by dynamic traffic behavior and multiple interacting operational factors.

Digital twin technology currently represents one of the most advanced simulation concepts in intelligent transport systems (H. Nguyen and T. Kim). A digital twin is a virtual representation of a physical transport system continuously updated using real-time operational data. Digital twins integrate AIS data, operational monitoring systems, predictive analytics, and simulation models into unified management environments.

Nguyen and Kim (H. Nguyen and T. Kim) state that digital twin technologies enable continuous operational monitoring, predictive analysis, and intelligent decision support in smart transportation systems. In inland navigation, digital twins may support traffic forecasting, operational optimization, and infrastructure management through real-time synchronization between physical and virtual systems.

The integration of Artificial Intelligence with simulation technologies creates intelligent predictive traffic management systems capable of dynamic operational optimization (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee), (A. Munim and H.-J. Schramm). AI algorithms can improve simulation accuracy, while simulation outputs can support the training and validation of predictive models. This combination significantly increases operational flexibility and analytical capabilities in inland navigation systems.

Simulation technologies therefore represent a critical component of digital transformation in inland waterway transport and provide important support for the development of intelligent navigation management systems (R. M. van der Zee and J. G. A. van der Vorst), (H. Nguyen and T. Kim).

5. Proposed Concept of Smart Inland Waterway Traffic Management

Based on the analysis of current technological trends and scientific studies, this article proposes a conceptual framework for smart inland waterway traffic management integrating Artificial Intelligence, AIS operational data, predictive analytics, and simulation technologies (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee), (H. Nguyen and T. Kim).

The proposed framework consists of several interconnected operational layers. The first layer focuses on data acquisition and operational monitoring. This layer continuously collects AIS data, vessel movement

information, infrastructure status data, and operational traffic information from navigation systems (International Maritime Organization). These data provide the foundation for predictive analysis and intelligent traffic management.

The second layer represents the data processing and analytical component. Operational data are processed and analysed using machine learning algorithms and predictive analytical models (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee), (A. Munim and H.-J. Schramm). The system identifies vessel movement patterns, operational anomalies, congestion risks, and possible traffic conflicts.

The third layer consists of predictive simulation and optimization modules. These modules integrate simulation technologies with AI-supported analytical models in order to forecast future traffic situations and evaluate alternative operational scenarios (R. M. van der Zee and J. G. A. van der Vorst), (J. Zhang, X. Chen, and L. Li). The simulation environment enables the prediction of vessel arrivals, estimation of waiting times, and evaluation of traffic management strategies.

Agent-based models and digital twin technologies play an important role within this framework (R. Boel and L. Mihaylova), (H. Nguyen and T. Kim). Agent-based simulation enables realistic modelling of vessel interactions and navigation behavior, while digital twins provide real-time synchronization between operational systems and virtual simulation environments.

An important component of the proposed framework is the decision-support interface for transport operators and navigation management centers. This interface provides traffic visualization, predictive operational warnings, congestion analysis, and optimization recommendations based on real-time analytical outputs (A. Munim and H.-J. Schramm).

The implementation of intelligent predictive traffic management systems may provide several operational benefits. Predictive traffic optimization can reduce operational delays, improve traffic coordination, increase infrastructure utilization efficiency, and support safer navigation operations (P. W. de Langen and K. B. Sharypova), (A. Munim and H.-J. Schramm). The integration of AI technologies with simulation models additionally enables adaptive operational planning under dynamic traffic conditions.

The proposed concept therefore represents an important step toward the development of intelligent inland navigation systems based on predictive analytics, operational simulation, and real-time traffic management technologies (H. Nguyen and T. Kim).

6. Discussion

The analysis presented in this article demonstrates that Artificial Intelligence and predictive simulation technologies have considerable potential for improving inland waterway traffic management systems (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee), (H. Nguyen and T. Kim). The integration of AI algorithms, AIS operational data, and simulation models enables more

accurate traffic prediction, dynamic operational planning, and intelligent decision support (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett), (A. Munim and H.-J. Schramm).

One of the most significant advantages of intelligent predictive traffic management systems is improved operational efficiency. AI-supported analytical models can optimize vessel scheduling, reduce waiting times at locks and terminals, and improve traffic coordination across inland waterway networks (P. W. de Langen and K. B. Sharypova). Simulation technologies additionally support operational scenario testing and infrastructure capacity analysis (R. M. van der Zee and J. G. A. van der Vorst), (J. Zhang, X. Chen, and L. Li).

Predictive traffic management systems also improve operational flexibility. Traditional rule-based traffic management approaches are often unable to respond effectively to rapidly changing operational conditions. In contrast, AI-supported systems continuously analyse operational data and dynamically adapt traffic management strategies according to current traffic conditions (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee).

Simulation technologies provide important analytical support for transport operators and infrastructure managers. Discrete-event simulation and agent-based models enable detailed analysis of operational bottlenecks, vessel interactions, and congestion situations (J. Zhang, X. Chen, and L. Li), (R. Boel and L. Mihaylova). Digital twin technologies further extend these capabilities by integrating real-time operational monitoring with predictive simulation environments (H. Nguyen and T. Kim).

Despite these advantages, several implementation challenges remain. One important limitation involves the quality and reliability of AIS operational data. Incomplete or inconsistent datasets may negatively affect prediction accuracy and simulation reliability (International Maritime Organization), (S. Capobianco, L. M. Millefiori, N. Forti, P. Braca, and P. Willett). Effective data management and data standardization therefore represent essential requirements for intelligent traffic management systems.

Another challenge involves the complexity and financial cost associated with the implementation of advanced AI systems and digital twin infrastructures (H. Nguyen and T. Kim). Intelligent predictive traffic management systems require significant technological investments, operational integration, and continuous maintenance.

The integration of Artificial Intelligence into inland navigation systems also creates increasing demands for cybersecurity and operational data protection. As transport systems become more interconnected and data-driven, protection against cyber threats becomes increasingly important for maintaining operational reliability and safety.

Future development in inland navigation will likely focus on greater integration of predictive analytics, AI-supported operational optimization, and digital twin technologies (R. Abduljabbar, H. Dia, S. Liyanage, and S. A. Bagloee), (H. Nguyen and T. Kim). Intelligent transport systems are expected to become essential components of

future inland waterway transport management and smart logistics infrastructure.

Conclusion

Inland waterway transport represents an important component of modern freight transportation and sustainable logistics systems. Growing transport demands, increasing operational complexity, and infrastructure limitations create the need for more advanced approaches to traffic management and operational coordination. The digital transformation of transport systems therefore plays a significant role in the future development of inland navigation.

The analysis presented in this article demonstrated that Artificial Intelligence, predictive analytics, and simulation technologies have considerable potential for improving inland waterway traffic management. Intelligent systems supported by operational data processing can improve traffic prediction, optimize vessel scheduling, reduce operational delays, and support more efficient decision-making processes. The use of AIS operational data enables continuous monitoring of vessel movements and contributes to more accurate forecasting of traffic situations.

The study also confirmed the importance of simulation technologies in inland navigation management. Simulation models enable detailed analysis of operational processes, infrastructure utilization, traffic capacity, and congestion situations without affecting real transport systems. Approaches such as discrete-event simulation, agent-based modelling, and digital twin technologies provide realistic representations of transport operations and create opportunities for testing alternative traffic management strategies under different operational conditions.

An important aspect identified in this research is the increasing role of intelligent and integrated transport management systems. The combination of real-time operational monitoring, predictive analytics, simulation modelling, and AI-supported decision-making creates a foundation for the development of smart inland navigation systems capable of adaptive and dynamic traffic management.

The proposed conceptual framework demonstrates how modern digital technologies can be integrated into inland waterway transport management. The framework combines operational data acquisition, predictive analysis, simulation environments, and decision-support tools into a unified intelligent management architecture. Such an approach may contribute to improved traffic coordination, more effective infrastructure utilization, and increased operational efficiency.

Despite the significant advantages of intelligent traffic management systems, several challenges remain. The effectiveness of predictive models depends heavily on the quality and reliability of operational data. In addition, the implementation of advanced digital systems requires substantial technological investments, infrastructure modernization, and long-term operational integration.

Cybersecurity and data protection also represent important considerations in the development of intelligent transport systems.

Future research should focus on improving predictive model accuracy, expanding the practical implementation of simulation technologies, and evaluating the operational performance of intelligent traffic management systems in real inland navigation environments. Additional attention should also be devoted to the integration of autonomous technologies and advanced real-time decision-support systems into inland waterway transport operations.

In conclusion, the integration of Artificial Intelligence, predictive analytics, and simulation technologies represents an important opportunity for improving inland waterway traffic management. Intelligent predictive systems have the potential to increase operational efficiency, improve traffic coordination, support safer navigation, and contribute to the further modernization of inland navigation systems.

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