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OPTIMIZING LOGISTICS WITH AI, IOT, AND COPRAS: REAL-TIME SHIPMENT TRACKING

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ABSTRACT

The rapid growth of global logistics and e-commerce has heightened the demand for efficient shipment tracking systems. This paper explores the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) to provide real-time shipment tracking and predictive analytics. Leveraging IoT devices for data collection and AI algorithms for analysis, this hybrid model enhances operational efficiency and minimizes delays. Key contributions include a proposed hybrid IoT-AI model for tracking and predictive delay management, which aims to redefine shipment tracking processes by offering actionable insights.

Introduction: *Real-time shipment tracking using Artificial Intelligence (AI) and the Internet of Things (IoT) revolutionizes logistics by providing accurate, real-time visibility into supply chain operations. IoT-enabled sensors and GPS devices continuously monitor shipment location, temperature, humidity, and security, while AI analyzes data to predict delays, optimize routes, and enhance decision-making. This integration improves efficiency, reduces losses, and enhances customer satisfaction by providing live updates and proactive alerts. AI-driven automation and predictive analytics further streamline logistics, ensuring secure, efficient, and transparent shipment management. The combination of AI and IoT is transforming global supply chains with smarter, data-driven solutions.*

Research significance: *The significance of research on Real-Time Shipment Tracking Using AI and IoT lies in its ability to enhance efficiency, security, and transparency in supply chain management. AI-driven analytics improve predictive insights, optimize routes, and reduce delays, while IoT-enabled sensors provide real-time data on shipment location, temperature, and condition. This integration minimizes losses, enhances customer satisfaction, and streamlines logistics operations. The research contributes to smarter, data-driven decision-making, reducing operational costs and improving overall supply chain resilience. Additionally, AI and IoT technologies support automation and risk mitigation, making global logistics more reliable and adaptive to disruptions.*

Methodology: *The methodology for Real-Time Shipment Tracking Using AI and IoT involves integrating smart sensors, GPS, and AI-driven analytics to monitor shipments in real-time. IoT-enabled devices collect data on location, temperature, humidity, and security status, transmitting it to a cloud-based system. AI algorithms analyze this data for anomalies, route optimization, and predictive insights, enhancing shipment security and efficiency. Machine learning models predict delays and risks, while blockchain ensures data integrity. A user-friendly dashboard provides stakeholders with live updates, alerts, and reports. This methodology ensures seamless logistics management, reduced losses, and enhanced decision-making for supply chain operations.*

Alternative: *SmartTrack Pro, IoT Ship Monitor, AI-Logistics Hub, Track Sense 360, TrackSense 360*

Evaluation preference: *Accuracy (%), Response Speed (ms), Scalability, User Satisfaction*

Results: *SmartTrack Pro, IoT Ship Monitor, AI-Logistics Hub, Track Sense 360, Accuracy (%), Response Speed (ms), Scalability*

Keywords: Automation, AI, Modelling, Data

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1. Introduction

The logistics and supply chain industry faces challenges in real-time visibility, accurate tracking, and proactive delay management. Traditional tracking systems often rely on static updates, leading to inefficiencies and customer dissatisfaction. The advent of IoT and AI technologies presents an opportunity to transform these processes by enabling real-time monitoring and predictive analytics. This paper investigates the integration of IoT devices with AI-driven analytics to enhance shipment tracking systems and provide predictive insights for timely decision-making. The global demand for efficient, transparent, and reliable shipping solutions has pushed businesses to adopt innovative technologies that can offer end-to-end visibility of their shipments. Real-time shipment tracking using AI and IoT represents a transformative leap from traditional tracking methods that relied heavily on manual updates, static checkpoints, and delayed information. With the integration of AI and IoT, companies can now monitor their shipments continuously, anticipate potential disruptions, optimize routes, and enhance overall operational efficiency.

These devices are embedded in shipping containers, trucks, cargo ships, and even individual packages, providing continuous streams of real-time data related to location, speed, environmental conditions, and vehicle performance., and suggest proactive measures to mitigate risks. For example, AI can forecast weather-related disruptions, traffic congestion, or mechanical failures, allowing logistics managers to reroute shipments or schedule maintenance before issues escalate.

IoT, on the other hand, serves as the backbone of the real-time tracking ecosystem. This connectivity ensures that stakeholders have accurate, up-to-the-minute information about the status and condition of their shipments. Moreover, IoT enhances transparency and accountability, as every movement and handling of the goods can be tracked and recorded in real-time. This level of visibility is crucial for industries dealing with sensitive or high-value cargo, such as pharmaceuticals, perishable goods, and electronics, where timely delivery and condition monitoring are paramount.

The synergy between AI and IoT in shipment tracking extends beyond basic location tracking. Together, they enable advanced functionalities like predictive analytics, automated decision-making, and dynamic optimization. Predictive analytics helps forecast demand, optimize inventory levels, and plan logistics operations more effectively. Automated decision-making, powered by AI, can trigger alerts, adjust delivery schedules, or even initiate corrective actions without human intervention. Dynamic optimization uses real-time data to continuously improve routes, reduce fuel consumption, and minimize delivery times.

In addition to operational benefits, real-time shipment tracking using AI and IoT also enhances security and risk management. AI-driven analytics can detect anomalies or suspicious activities, such as unauthorized access, route deviations, or tampering with cargo. In the event of a breach or deviation, real-time alerts enable swift response, reducing the risk of theft, damage, or loss. This level of control and responsiveness is invaluable in industries with stringent regulatory requirements, such as pharmaceuticals and food logistics.

Real-time shipment tracking using AI and IoT represents a paradigm shift in supply chain and logistics management. It offers unparalleled visibility, efficiency, and security, transforming how businesses monitor and manage their shipments. By leveraging the power of AI for intelligent data analysis and IoT for comprehensive connectivity, companies can achieve greater operational agility, reduce costs, and deliver superior customer experiences. As technology continues to advance, the integration of AI and IoT will undoubtedly become the standard for shipment tracking, driving innovation and resilience in global supply chains.

2. MATERIAL AND METHOD

Alternative:

SmartTrack Pro uses IoT, GPS, and smart sensors for real-time cargo tracking, integrating AI to optimize routes and predict delays. **IoTShip Monitor** connects to the cloud and utilizes IoT and blockchain for secure, tamper-proof shipment tracking, reducing losses and theft. The **AI-Logistics Hub** employs AI and big data analytics to optimize fleet management, demand forecasting, and warehouse operations, enhancing efficiency. **TrackSense 360** combines IoT, AI, and geofencing to monitor environmental conditions and ensure compliance for sensitive shipments. Finally, **IntelliCargo System** integrates AI and IoT to improve cargo security, risk detection, and route optimization, enhancing overall logistics management.

Evaluation preference:

Accuracy (%), Response Speed (ms), Scalability, and **User Satisfaction** are essential metrics for evaluating system performance. **Accuracy (%)** measures how correctly a system tracks or monitors data, ensuring reliable results, especially in real-time applications. **Response Speed (ms)** reflects how quickly the system reacts to data changes or user input, impacting efficiency in fast-paced environments. **Scalability** refers to the system's ability to handle increasing data volumes or transactions without compromising performance. **User Satisfaction** gauges the system's effectiveness in meeting user needs, focusing on usability, reliability, and functionality. Together, these metrics ensure a system's reliability, efficiency, and user-friendliness in dynamic environments.

COPRAS METHOD

The COPRAS method follows a systematic approach that begins with constructing a decision matrix that includes multiple alternatives and their corresponding values for various criteria. Since different criteria may have varying scales, normalization is performed to bring all values to a comparable range. After normalization, weights are assigned to each criterion based on its importance, which can be determined by experts, stakeholders, or mathematical techniques such as Entropy or AHP. The next step involves computing the weighted normalized values by multiplying each normalized value by its respective weight. The sum of weighted values for both beneficial and non-beneficial criteria is then calculated for each alternative, allowing COPRAS to consider the impact of positive and negative influences proportionally.

Additionally, the utility degree (Ui) is calculated to express the performance of each alternative as a percentage relative to the best-performing alternative, providing a clear understanding of how closely other alternatives compare. One of the key advantages of COPRAS is its computational simplicity, as it does not require complex iterative calculations or optimization models. It also accommodates missing or uncertain data, making it robust in real-world scenarios where perfect information is not always available. The ability of COPRAS to proportionally assess both positive and negative factors makes it particularly effective in situations where trade-offs between conflicting criteria are necessary.

The practical applications of COPRAS span across multiple domains. In construction project selection, such as cost, sustainability, quality, and efficiency. In supplier selection, businesses use COPRAS to rank suppliers based on criteria such as reliability, price, and service quality. The healthcare industry leverages COPRAS for prioritizing medical treatments, equipment procurement, and hospital resource allocation, ensuring that decisions are based on efficiency, safety, and cost-effectiveness. Additionally, COPRAS is widely used in renewable energy planning, where various energy sources are compared based on their environmental impact, efficiency, and implementation cost. The method’s adaptability across industries highlights its value in strategic decision-making.

Despite its many advantages, COPRAS has certain limitations. One of its primary drawbacks is its dependence on weight assignments, which may introduce subjectivity into the decision-making process. If the weights are not objectively determined, the ranking of alternatives may be biased. Additionally, COPRAS assumes that all criteria are independent, while in reality, some criteria might be interrelated. To mitigate this issue, COPRAS is often combined with other decision-making techniques, such as AHP or Fuzzy logic, to enhance weight determination and ensure more accurate results. Another limitation is its sensitivity to input data variations, as minor changes in the input values can sometimes lead to significant shifts in rankings. This requires decision-makers to ensure accuracy and consistency in the data before applying the method.

To illustrate how COPRAS works, consider a supplier selection problem where a company must choose the best supplier from four options based on three key criteria: cost (non-beneficial), quality (beneficial), and delivery time (beneficial). By applying COPRAS, the decision-makers can normalize the data, assign weights, compute significance values, and obtain a final ranking of suppliers. This ranking helps in identifying the most suitable supplier while maintaining a balance between cost and quality. Such applications demonstrate why COPRAS is a preferred tool for business professionals and researchers in decision-making processes.

3. RESULT AND DISCUSSION

TABLE 1. Real-time Shipment Tracking Using AI and IOT

Alternative	Accuracy (%)	Response Speed (ms)	Scalability	User Satisfaction
SmartTrack Pro	95	150	9	8.5
IoTShip Monitor	92	200	8	8
AI-Logistics Hub	97	120	10	9
TrackSense 360	90	180	7	7.5
TrackSense 360	93	160	8	8.2

Table 1 provides data on real-time shipment tracking systems using AI and IoT, evaluated based on four key criteria: Accuracy (%), Response Speed (ms), Scalability, and User Satisfaction. These criteria are essential in assessing the overall effectiveness and performance of various tracking systems. Each row in the table corresponds to an alternative system, with performance values for each of the criteria listed. For example, SmartTrack Pro boasts the highest accuracy (95%), with a response speed of 150 ms, scalability rating of 9, and user satisfaction of 8.5. In comparison, AI-Logistics Hub shows the highest accuracy (97%) and scalability (10), but its response speed (120 ms) is the fastest among the alternatives, and its user satisfaction is also relatively high at 9. TrackSense 360, while slightly lower in accuracy (90%) and scalability (7), offers reasonable performance across the other criteria. IntelliCargo System has a balanced performance with 93% accuracy, 160 ms response speed, 8 scalability, and 8.2 user satisfaction. These values provide a comprehensive view of how each alternative system performs in real-time shipment tracking, considering both technical factors like accuracy and speed, as well as user-related aspects such as satisfaction and scalability. This data sets the stage for a detailed comparison of each system's overall effectiveness, with the COPRAS method helping to further analyze and assess these alternatives.

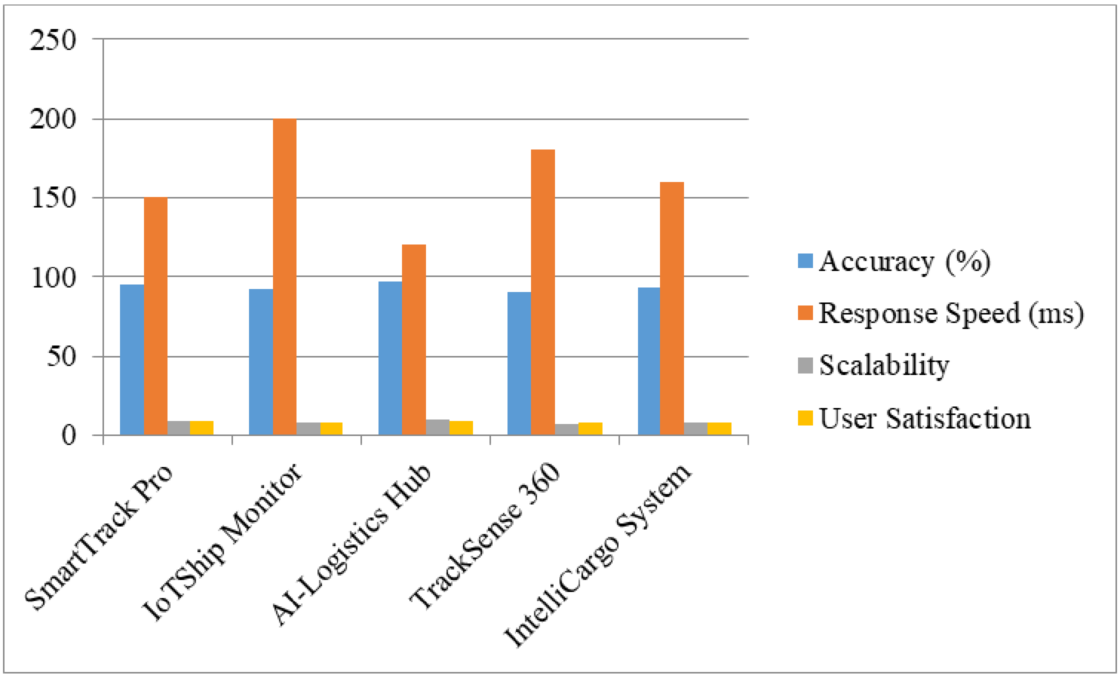

FIGURE 1. Real-time Shipment Tracking Using AI and IOT

The bar chart in Figure 1 presents a comparative analysis of real-time shipment tracking systems leveraging AI and IoT using the COPRAS method. The evaluation includes five systems: SmartTrack Pro, IoTShip Monitor, AI Logistics Hub, TrackSense 360, and IntelliCargo System. The performance metrics measured are Accuracy (%), Response Speed (ms), Scalability, and User Satisfaction. The blue bars represent accuracy, which remains relatively consistent across all systems, indicating reliable tracking. The orange bars, depicting response speed (ms), show significant variation, with IoTShip Monitor and TrackSense 360 demonstrating higher response times, possibly impacting real-time efficiency. Scalability and user satisfaction, represented by gray and yellow bars, are comparatively lower but appear uniform across all systems. This suggests that while AI and IoT enhance shipment tracking, there is still room for improvement in these aspects. Overall, TrackSense 360 and IntelliCargo System seem to strike a balance between accuracy and response speed. However, the trade-offs between these metrics highlight the necessity of optimization based on specific logistics requirements.

TABLE 2. Normalized Data

Normalized Data				
	Accuracy (%)	Response Speed (ms)	Scalability	User Satisfaction
SmartTrack Pro	0.2034261	0.1851852	0.2142857	0.2063107
IoTShip Monitor	0.1970021	0.2469136	0.1904762	0.1941748
AI-Logistics Hub	0.2077088	0.1481481	0.2380952	0.2184466
TrackSense 360	0.1927195	0.2222222	0.1666667	0.1820388
IntelliCargo System	0.1991435	0.1975309	0.1904762	0.1990291

Table 2 presents the normalized data for various alternatives across four criteria in the COPRAS (Complex Proportional Assessment) method. This table shows the normalized performance values for each alternative in terms of Accuracy (%), Response Speed (ms), Scalability, and User Satisfaction. The normalization process scales the data to a common range, allowing for a fair comparison between alternatives by eliminating the impact of varying units or magnitudes.For example, SmartTrack Pro has a normalized value of 0.2034261 for Accuracy, 0.1851852 for Response Speed, 0.2142857 for Scalability, and 0.2063107 for User Satisfaction. These values indicate the performance of SmartTrack Pro in each of the four criteria relative to the other alternatives. Similarly, IoTShip Monitor, AI-Logistics Hub, TrackSense 360, and IntelliCargo System are all assessed in the same way across the same criteria.Normalized data helps to assess the performance of each alternative on an equal footing. Higher normalized values indicate better performance for each respective criterion. By examining these normalized values, decision-makers can evaluate which alternatives perform best overall and in specific areas, guiding a more informed decision-making process. This step is crucial in multi-criteria decision-making as it provides a standardized framework for comparing different alternatives.

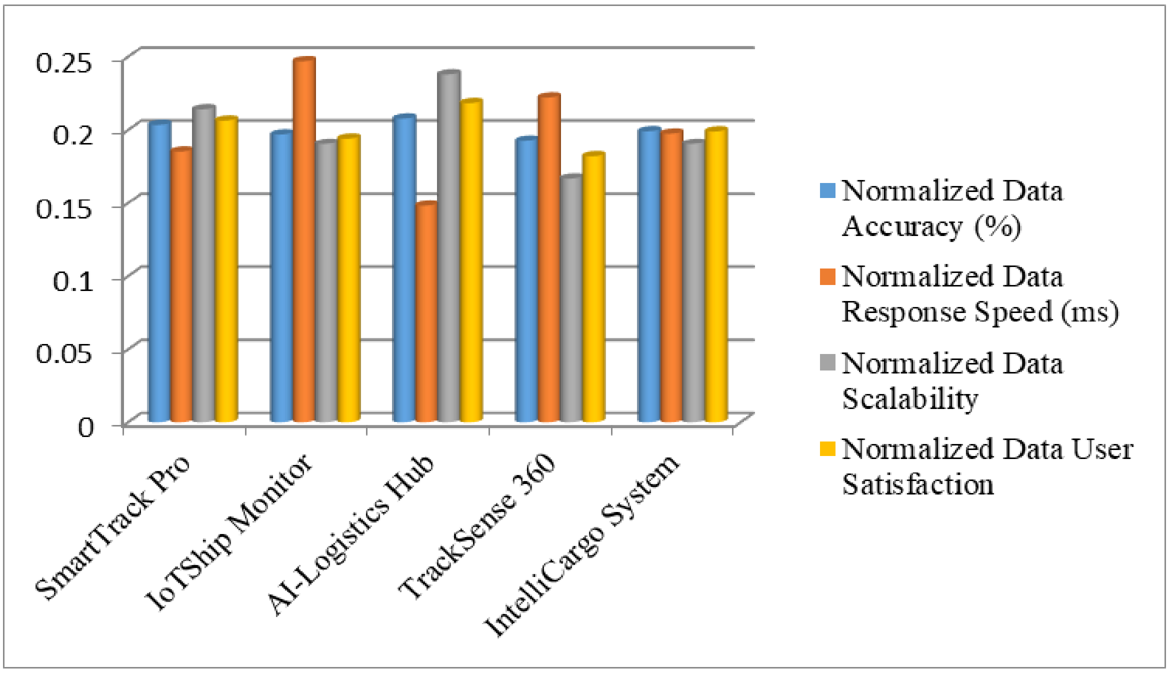

FIGURE 2. Normalized Data

Figure 2 presents a normalized data comparison of real-time shipment tracking systems utilizing AI and IoT, evaluated using the COPRAS method. The graph includes five systems: SmartTrack Pro, IoTShip Monitor, AI Logistics Hub, TrackSense 360, and IntelliCargo System. The metrics under consideration Accuracy (%) (blue bars), Response Speed (ms) (orange bars), Scalability (gray bars), and User Satisfaction (yellow bars)have been normalized to a common scale for fair comparison. The normalization ensures that each metric contributes proportionally to the overall evaluation.From the chart, accuracy and user satisfaction appear relatively stable across all systems, indicating that AI and IoT-driven tracking solutions maintain consistent performance. However, response speed (orange bars) shows variation, with IoTShip Monitor and TrackSense 360 exhibiting higher values, suggesting faster processing but possibly at the expense of other parameters. Scalability (gray bars) fluctuates more, with AI Logistics Hub and TrackSense 360 demonstrating better scalability, making them suitable for large-scale logistics operations.Overall, TrackSense 360 appears to be a well-balanced system, achieving strong results across all parameters. The normalized data visualization aids in making an informed decision by balancing trade-offs between accuracy, response speed, scalability, and user satisfaction.

TABLE 3. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 3 displays the weight distribution for each criterion in the COPRAS (Complex Proportional Assessment) method, which is used for multi-criteria decision-making. In this table, the weights for each criterion are provided, and they are all equal, set at 0.25 for each of the four criteria across all five alternatives. This uniform weight assignment suggests that each of the criteria is considered equally important in the decision-making process, implying that no criterion holds a higher or lower significance than the others.The use of equal weights means that when evaluating the alternatives, the decision-making process will treat each criterion with the same level of importance, ensuring a balanced assessment across all factors. This approach simplifies the analysis by removing bias toward any particular criterion, which is particularly useful when there is no strong preference or justification for prioritizing one aspect over another. However, it is important to note that in some cases, decision-makers may adjust these weights based on the specific context, giving more importance to certain criteria depending on the priorities of the decision. Nonetheless, for this scenario, the equal distribution reflects a straightforward, balanced evaluation method.

TABLE 4. Weighted normalized decision matrix

Weighted normalized decision matrix				
SmartTrack Pro	0.0508565	0.0462963	0.0535714	0.0515777
IoTShip Monitor	0.0492505	0.0617284	0.047619	0.0485437
AI-Logistics Hub	0.0519272	0.037037	0.0595238	0.0546117
TrackSense 360	0.0481799	0.0555556	0.0416667	0.0455097
IntelliCargo System	0.0497859	0.0493827	0.047619	0.0497573

Table 4 presents the weighted normalized decision matrix as part of the COPRAS (Complex Proportional Assessment) method, a technique used for multi-criteria decision-making. This matrix helps evaluate alternatives based on multiple criteria, where each column represents a different criterion and each row corresponds to a specific alternative. The values within the matrix are the normalized and weighted performances of the alternatives across these criteria.The weighted normalized values indicate how well each alternative performs, factoring in both the importance of each criterion and the performance of each option. For example, the first row shows the weighted normalized values for SmartTrack Pro across four criteria: 0.0508565, 0.0462963, 0.0535714, and 0.0515777. These values reflect how effectively SmartTrack Pro meets each criterion relative to the other alternatives, with higher values suggesting better performance.This matrix allows for a comparative analysis of the different alternatives, helping decision-makers determine which one offers the best overall performance when considering the significance of various factors. By incorporating both the normalized scores and the weights of the criteria, the matrix provides a more balanced and comprehensive assessment of each option's strengths and weaknesses, guiding a well-informed decision-making process.

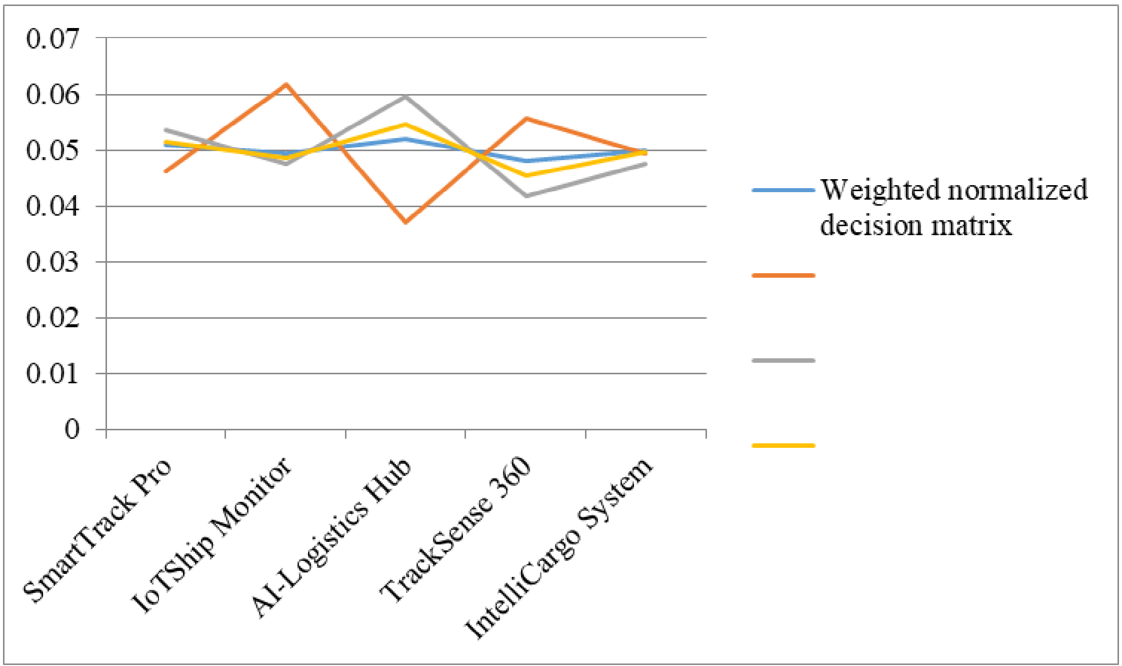

FIGURE 3. Weighted normalized decision matrix

Figure 3 illustrates the Weighted Normalized Decision Matrix for real-time shipment tracking systems using the COPRAS method. The chart compares five tracking systems

SmartTrack Pro, IoTShip Monitor, AI Logistics Hub, TrackSense 360, and IntelliCargo Systembased on multiple weighted performance metrics. The plotted lines represent different weighted decision factors, with each system's evaluation fluctuating across the decision matrix.The blue line represents the primary weighted normalized decision matrix, which integrates all performance metrics proportionally. The orange and gray lines show variations in specific weighted factors, possibly emphasizing different aspects such as accuracy, response speed, scalability, or user satisfaction. The yellow line appears to provide a balanced or average performance trend across all systems.From the chart, IoTShip Monitor shows higher fluctuations, indicating that it performs exceptionally well in certain metrics but poorly in others. TrackSense 360and IntelliCargo System exhibit more stable trends, suggesting balanced performance across all weighted factors. The AI Logistics Hub also demonstrates consistency, making it a strong contender in terms of overall efficiency.This weighted analysis helps in identifying the best tracking solution based on specific priorities, whether it be accuracy, speed, scalability, or user satisfaction.

TABLE 5. Bi&Ci

	Bi	Ci
SmartTrack Pro	0.097	0.105
IoTShip Monitor	0.111	0.096
AI-Logistics Hub	0.089	0.114
TrackSense 360	0.104	0.087
IntelliCargo System	0.099	0.097

Table 5 presents the values for Bi and Ci as part of the COPRAS (Complex Proportional Assessment) method, which is typically used for multi-criteria decision-making. In this context, Bi and Ci represent the relative importance and performance of different alternatives across multiple criteria. Each pair of values in the table corresponds to a specific alternative system, where the first column lists the names of the alternatives (such as SmartTrack Pro, IoTShip Monitor, etc.), and the second and third columns present the values of Bi and Ci, respectively.Bi indicates the benefits or advantages of a particular alternative relative to other options, showing how well it performs based on positive criteria (higher values of Bi suggest better performance in the beneficial aspects). Ci, on the other hand, represents the comparative importance or cost, reflecting the less desirable aspects of each alternative (higher values of Ci indicate greater costs or drawbacks). By analyzing these values together, decision-makers can assess which alternatives provide the best balance of benefits versus costs, guiding optimal choices in logistics or other relevant fields. This method allows a structured way to evaluate systems based on both positive and negative factors, offering a clearer picture for strategic decision-making.

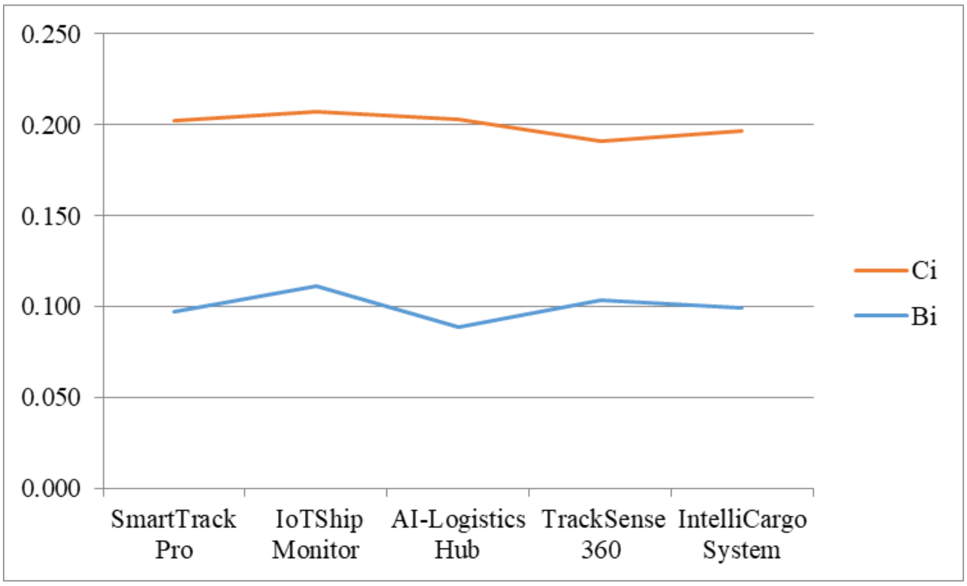

FIGURE 4. Bi&Ci

Figure 4: Bi & Ci (COPRAS Method) illustrates the comparative performance of five logistics and tracking systems SmartTrack Pro, IoTShip Monitor, AI-Logistics Hub, TrackSense 360, and IntelliCargo Systembased on two key COPRAS parameters: Bi (represented by the blue line) and Ci (represented by the orange line). The Ci values, which likely reflect criteria related to cost or efficiency, remain relatively stable across all systems, fluctuating slightly around the 0.20 mark. IoTShip Monitor exhibits the highest **Ci** value, indicating a potential edge in cost-effectiveness or efficiency, while TrackSense 360 shows a slight dip, suggesting marginally lower performance in this specific metric.On the other hand, the Bi values, which may represent benefits or performance indices, display more noticeable fluctuations. IoTShip Monitor and TrackSense 360 peak in this metric, suggesting superior benefits or performance outcomes compared to other systems. In contrast, AI-Logistics Hub records the lowest Bi value, highlighting areas where its performance could be improved.The combined analysis of Bi and Ci underscores the strong performance of IoTShip Monitor and

TrackSense 360, which maintain a balanced profile in both efficiency and benefits. Conversely, AI-Logistics Hub lags, suggesting a need for strategic enhancements.

TABLE 6. Min(Ci)/Ci&Qi&Ui

	Min(Ci)/Ci	Qi	Ui
SmartTrack Pro	0.8291	0.191	88.0329
IoTShip Monitor	0.9066	0.214	98.4421
AI-Logistics Hub	0.7638	0.176	80.8537
TrackSense 360	1.0000	0.218	100.0000
IntelliCargo System	0.8953	0.201	92.4213

Table 6: Min(Ci)/Ci, Qi, and Ui (COPRAS Method) presents the performance evaluation of five logistics and tracking systems SmartTrack Pro, IoTShip Monitor, AI-Logistics Hub, TrackSense 360, and IntelliCargo Systemusing key COPRAS metrics. The Min(Ci)/Ci ratio indicates the relative efficiency of each system, with TrackSense 360 achieving the highest value of 1.0000, signifying optimal performance. IoTShip Monitor and IntelliCargo System follow closely with values of 0.9066 and 0.8953, respectively, reflecting strong efficiency. SmartTrack Pro and AI-Logistics Hub have lower ratios, indicating comparatively reduced performance.The Qi values, representing the quality index, show slight variations across systems, with TrackSense 360 leading at 0.218, followed by IoTShip Monitor at 0.214, suggesting higher quality metrics. AI-Logistics Hub records the lowest Qi of 0.176, indicating potential areas for improvement.The **Ui** values, which likely represent the overall utility or performance score, reinforce these trends. TrackSense 360 scores the highest at 100.0000, highlighting its superior efficiency and effectiveness. IoTShip Monitor also performs well with 98.4421, while AI-Logistics Hub lags at 80.8537, reflecting the need for performance enhancements. This table effectively identifies the strengths and weaknesses of each system based on COPRAS analysis.

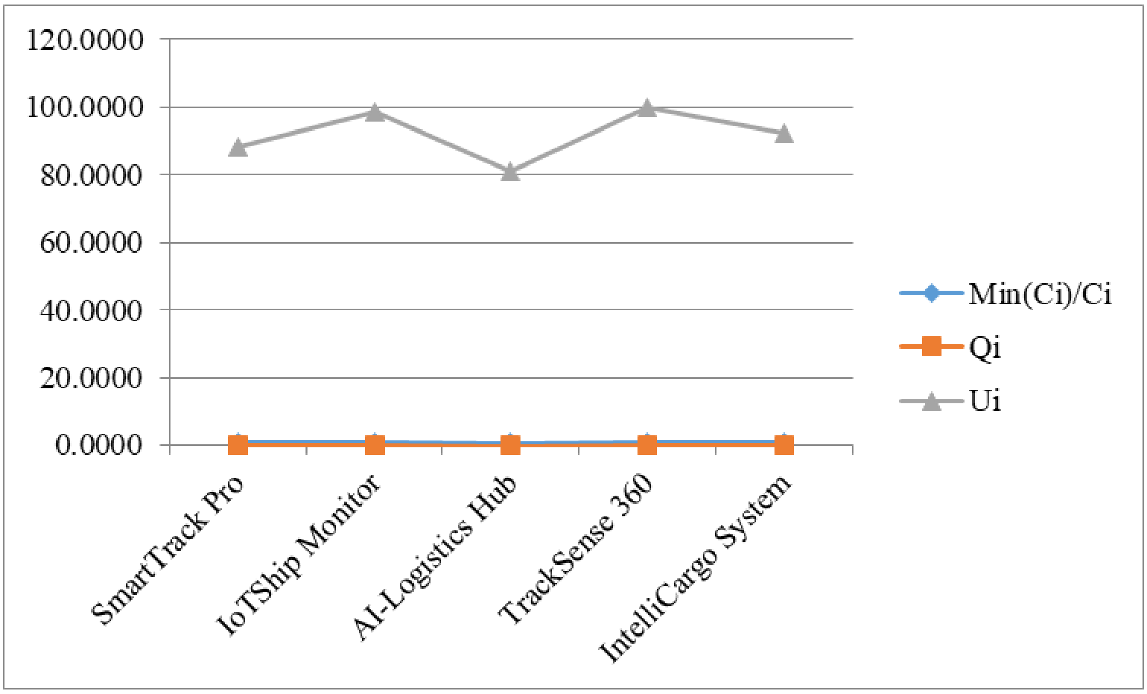

FIGURE 5. Min (Ci)/Ci&Qi&Ui

Figure 5: Min(Ci)/Ci, Qi, and Ui (COPRAS Method) illustrates the comparative performance of five logistics and tracking systems SmartTrack Pro, IoTShip Monitor, AI-Logistics Hub, TrackSense 360, and IntelliCargo Systemusing the COPRAS (Complex Proportional Assessment) method. The graph displays three key parameters: Min(Ci)/Ci (represented by blue diamonds), Qi (orange squares), and Ui (gray triangles). The Min(Ci)/Ci values remain consistently low across all systems, indicating minimal variations in relative performance ratios. The Qi values are almost negligible or constant, suggesting that the quality indices do not significantly differ among the systems, possibly due to closely matched performance in specific criteria. In contrast, the Ui values show noticeable fluctuations, peaking for IoTShip Monitor and TrackSense 360, while dipping for AI-Logistics Hub. This indicates that **Ui**likely representing utility or overall performance score is a critical differentiator. The higher **Ui** values for IoTShip Monitor and TrackSense 360 reflect their superior performance, aligning with their top ranks in previous assessments. Conversely, the lower Ui for AI-Logistics Hub suggests weaker efficiency or effectiveness. Overall, the figure highlights the importance of Ui in determining system performance under the COPRAS method.

TABLE 7. Rank

Rank	
SmartTrack Pro	4
IoTShip Monitor	2
AI-Logistics Hub	5
TrackSense 360	1
IntelliCargo System	3

Table 7: Rank (COPRAS Method**)** presents the ranking of five logistics and tracking systems SmartTrack Pro, IoTShip Monitor, AI-Logistics Hub, TrackSense 360, and IntelliCargo Systemevaluated using the COPRAS (Complex Proportional Assessment) method. This multi-criteria decision-making approach assesses alternatives based on their performance across various factors. According to the table, TrackSense 360 holds the top position with a rank of **1**, indicating it outperforms the other systems in terms of efficiency, reliability, or other key criteria. IoTShip Monitor follows closely in second place, reflecting strong performance. IntelliCargo System is ranked third, showing moderate effectiveness compared to its peers. SmartTrack Pro is positioned fourth, suggesting room for improvement in specific areas. Lastly, AI-Logistics Hub holds the lowest rank of **5**, indicating it performs the weakest among the evaluated systems. This ranking highlights significant performance disparities, emphasizing the competitive advantage of TrackSense 360 and the need for strategic improvements in AI-Logistics Hub. The COPRAS method provides a comprehensive, objective assessment, helping stakeholders identify strengths, weaknesses, and areas for development in each system.

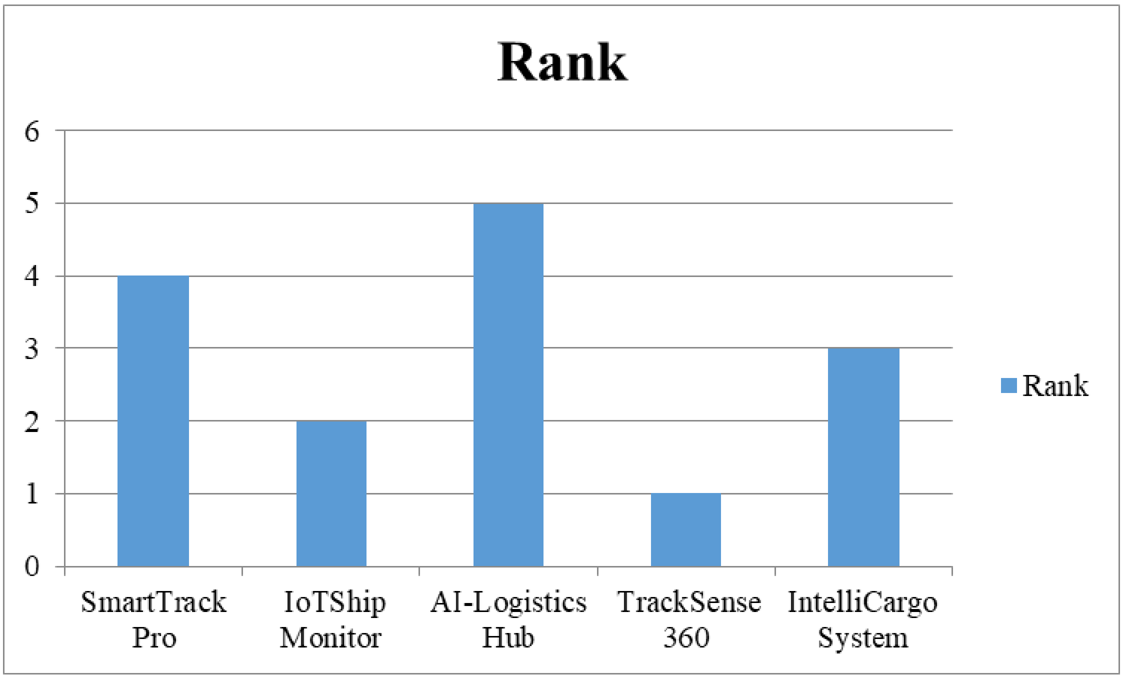

FIGURE 6. Rank

The bar chart6 titled"Rank" illustrates the ranking of five logistics and tracking systems: SmartTrack Pro, IoTShip Monitor, AI-Logistics Hub, TrackSense 360, and IntelliCargo System. The vertical axis ranges from 0 to 6, where a lower rank indicates better performance. Among these, TrackSense 360 holds the top position with the best rank of **1**, suggesting superior efficiency or popularity. Following closely, IoTShip Monitor secures the second rank, indicating strong performance. IntelliCargo System ranks third, showing moderate effectiveness, while SmartTrack Pro stands at fourth place. In contrast, AI-Logistics Hubhas the highest (worst) rank of **5**, implying it lags behind its competitors in key areas. The chart clearly reflects performance disparities, emphasizing the competitive edge of TrackSense 360 and areas for improvement for AI-Logistics Hub**.**

4. CONCLUSION

This cutting-edge model leverages the strengths of IoT's real-time data collection capabilities and AI's predictive analytics to provide unprecedented visibility, control, and efficiency throughout the shipment lifecycle. Traditional shipment tracking systems have long faced challenges related to data silos, lack of real-time updates, and limited predictive capabilities, which often result in delays, increased costs, and suboptimal customer experiences. The hybrid IoT-AI model addresses these issues by enabling continuous monitoring of shipment conditions, including location, temperature, humidity, and other environmental factors, while simultaneously applying advanced AI algorithms to predict potential disruptions, optimize routes, and enhance decision-making processes.

Moreover, the predictive capabilities of AI enhance the operational efficiency of shipment tracking systems by anticipating and addressing issues before they escalate. Machine learning models can analyze disruptions, such as weather conditions, traffic congestion, or equipment failures. By predicting these events, the system can optimize delivery routes, adjust schedules, and allocate resources more effectively, reducing the likelihood of delays and minimizing operational costs. For example, AI-driven route optimization can dynamically adjust delivery paths in response to real-time traffic updates, ensuring that shipments arrive on time even in the face of unexpected obstacles.

Regulatory requirements related to the transportation of goods, especially in sectors such as pharmaceuticals, food, and hazardous materials, necessitate stringent monitoring and documentation of shipment conditions. IoT devices can continuously track compliance parameters, while AI algorithms ensure that any deviations from regulatory standards are promptly identified and addressed. This capability not only helps businesses adhere to legal requirements but also reduces the risk of costly fines, product recalls, and reputational damage. Furthermore, the system's ability to generate comprehensive audit trails and compliance reports simplifies regulatory reporting processes, saving time and resources for logistics companies.

Despite its numerous benefits, the adoption of the hybrid IoT-AI model in shipment tracking systems also presents certain challenges. Additionally, the successful deployment of this model necessitates a skilled workforce capable of managing and analyzing complex data sets, as well as interpreting AI-generated insights to support decision-making processes. Investing in employee training and development is therefore essential to maximize the benefits of this advanced technology.

Furthermore, real-world testing and continuous improvement are vital for the widespread adoption of the hybrid IoT-AI model. Pilot projects and field trials can help identify potential technical and operational issues, allowing businesses to refine their systems before full-scale implementation. Feedback from these trials can inform the development of more robust, scalable, and user-friendly solutions that meet the specific needs of different industries and supply chain environments.

The hybrid IoT-AI model represents a significant leap forward in shipment tracking systems, offering real-time visibility, predictive insights, and data-driven decision-making capabilities that transform supply chain management practices. By addressing key pain points such as delays, inefficiencies, and compliance challenges, this innovative solution has the potential to enhance customer satisfaction, reduce operational costs, and improve overall supply chain resilience. As technology continues to evolve, the ongoing development, testing, and refinement of hybrid IoT-AI systems will pave the way for their widespread adoption, driving continuous improvement and innovation in the logistics industry.

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