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Review

The Role of Artificial Intelligence (AI) in the Future of Forestry Sector Logistics

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Abstract: Background: The forestry industry plays an important role in the economy and environmental sustainability, facing significant logistical challenges such as the geographical dispersion of plantations, the variability of raw materials, and high transportation costs. Artificial Intelligence (AI) emerges as a promising tool to optimize logistics processes, contributing to the reduction in costs, waste, and environmental impacts. Methods: This study combines a literature review and case analysis to assess the impact of AI on forestry logistics. Machine Learning algorithms, optimization systems, and monitoring tools based on the Internet of Things (IoT) and computer vision were analyzed to assess impacts in areas such as transportation planning, inventory management, and forest monitoring. Results: The results demonstrated that optimization algorithms reduced transportation costs and carbon emissions. Predictive tools proved to be effective in inventory management, while real-time monitoring with drones and sensors allowed for the identification and mitigation of environmental risks, such as pests and fires, promoting greater operational efficiency. Conclusions: AI has great potential to transform forestry logistics, improving efficiency and sustainability. However, its implementation faces barriers such as high upfront costs and limitations in data collection, and strategic collaborations are needed to maximize its impact.

Keywords: Artificial Intelligence (AI); logistics; forestry industry; sustainability

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1. Introduction

The forestry sector faces increasing pressure to enhance operational efficiency and sustainability amid rising global demands for wood products and stricter environmental regulations. Traditional logistics approaches often fail to address the sector's unique challenges, such as geographical dispersion and resource variability, necessitating innovative solutions. Artificial Intelligence (AI) offers transformative potential to optimize these processes, yet its application in forestry logistics remains underexplored. This research is motivated by the need to bridge that gap, providing a comprehensive evaluation of AI's role in improving logistics efficiency and sustainability. The contribution of this study lies in its systematic synthesis of the existing literature and case studies, offering actionable insights for stakeholders and identifying future research directions to advance AI adoption in the forestry sector. Within this study, AI encompasses a broad range of technologies capable of independent reasoning and decision-making, with Machine Learning (ML)—particularly its predictive analytics capabilities—considered a key subset. AI systems mimic human cognitive functions, such as learning from data, adapting to new inputs, and making autonomous decisions, distinguishing them from traditional rule-based systems. While AI includes advanced applications like natural language processing and image recognition, ML's established role in pattern recognition and forecasting is central to logistics optimization, offering actionable insights from complex datasets.

The forest chain plays a central role in several global economies, standing out not only for its economic relevance but also for its significant impact on environmental and social sustainability [1]. This sector is part of a vast value chain, which ranges from the production of raw materials, such as wood and cellulose, to the manufacture of finished products, including paper, furniture, or biomass to energy [2]. In Portugal, the forestry sector is particularly relevant, representing one of the country's main exporting and employing industries [3]. However, this sector faces complex logistical challenges, ranging from efficient resource management to optimizing transport, storage, and distribution chains. These challenges, when poorly managed, can result in high costs, wasted resources, and significant environmental impacts.

In the current context, characterized by increasing pressure to integrate sustainable and efficient practices, technological innovation emerges as an indispensable tool to overcome traditional obstacles in forestry logistics. Artificial Intelligence (AI), in particular, has proven to be a powerful ally in transforming processes and business models across different sectors [4]. Its ability to process large volumes of data, identify complex patterns, and offer predictive solutions places AI at the forefront of the logistics revolution, opening up new possibilities for the forestry chain [5,6]. In this sense, the application of AI-based tools can optimize operational efficiency and also promote more sustainable and responsible practices [7].

The logistical challenges faced by the forestry chain are multifaceted and include, among others, the transportation of bulky and heterogeneous materials, the management of stocks subject to deterioration, and the coordination of operations in geographically dispersed areas [8]. Additionally, the inherent variability of forest production, conditioned by climatic, seasonal, and biological factors, requires highly adaptable and resilient logistics systems [9]. The traditional manual and fragmented approach to these challenges often proves insufficient, especially given the increasing complexity of global supply chains [10].

AI applications range from demand forecasting, enabling more efficient resource management, to the automation of repetitive tasks, such as route planning and warehouse management [11]. In the forestry supply chain, the application of these technologies remains, however, still in its infancy, although there are already success stories that demonstrate their transformative potential [12]. For example, AI-based systems have been used to predict forest growth, optimize timber harvesting and transportation, and monitor forest health in real time using data from satellites and drones, improving operational efficiency and contributing to environmental conservation by enabling more sustainable management of natural resources [13].

Despite its potential, the implementation of AI technologies in the forestry chain still faces significant barriers, including the high initial cost of adoption, resistance to change by organizations, and the need to develop specialized technical skills [14]. Additionally, effectively integrating AI into existing logistics systems requires a robust and accessible digital infrastructure, something that not all companies in the sector have [15]. Therefore, a joint effort between industry, government, and academic institutions becomes necessary to encourage the adoption of these technologies, promoting incentive policies, training, and capacity development [16].

Another relevant aspect to be considered when applying AI in the forestry production chain is the ethical and social issue. The use of AI algorithms for decision-making raises concerns related to transparency, fairness, and accountability. For example, the automation of logistics processes can lead to job losses in certain areas, affecting rural communities dependent on the forestry chain [17]. Therefore, the implementation of these technologies must be accompanied by an ethical and inclusive debate, ensuring that the benefits of digital transformation are shared equitably and that potential negative consequences are mitigated [18].

This article seeks to examine the role of Artificial Intelligence (AI) in optimizing logistics processes within the forestry sector, highlighting the benefits, challenges, and implications of this technological transformation. The analysis centers on three primary objectives: (1) identifying areas of forestry logistics that can benefit from AI applications, (2) presenting practical examples of AI-based solutions and their impacts, and (3) discussing the barriers and opportunities associated with the adoption of these technologies in the sector. To achieve this, a review of the existing literature was conducted, supplemented by case study analyses and the identification of emerging trends.

AI is necessary to distinguish from traditional optimization methods, such as heuristic algorithms (e.g., A-Star) or linear programming, which seek optimal solutions based on predefined rules but lack adaptive learning. AI's unique advantage lies in its ability to autonomously learn from data, adapt to dynamic conditions (e.g., weather, traffic), and handle unstructured inputs (e.g., satellite imagery), surpassing traditional methods' static frameworks. For instance, while A-Star optimizes routes efficiently, ML can predict demand shifts, offering proactive rather than reactive solutions, critical for forestry's variability.

Throughout the manuscript, specific examples include regional and country contexts to balance broad conceptual themes with localized applicability. For instance, in Section 4.2.1, the eucalyptus plantation case study from Uruguay is contextualized with its relevance to Portugal, while Section 4.2.2 details drone monitoring in Portugal's pine forests. Additional examples in Section 3, such as Sweden's use of ML for transport optimization and India's AI-driven biodiversity monitoring, provide geographical diversity, enhancing the framework's extrapolability. Figure 1, presented at the end of this section, visually illustrates how AI technologies integrate into each forestry logistics stage, enhancing readability and conceptual clarity.

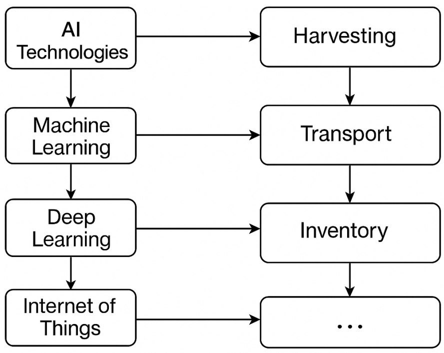

Figure 1. Conceptual framework illustrating the integration of AI technologies—such as Machine Learning, Deep Learning, and the Internet of Things—into key stages of forestry logistics, including harvesting, transport, and inventory management.

2. Methods

2.1. Methodological Approach

This study adopts a mixed-methods approach, integrating a systematic literature review (SLR) with case study analysis to evaluate the role of AI in forestry logistics. The SLR was conducted following a systematic protocol to ensure an unbiased and representative sample, in accordance with best practice guidelines [19]. The Scopus, Web of Science, and IEEE Xplore databases were selected for their extensive coverage of peer-reviewed publications in engineering, environmental science, and technology. The search spanned the period from 2010 to 2024, reflecting the rapid evolution of AI technologies during this timeframe (Figure 2).

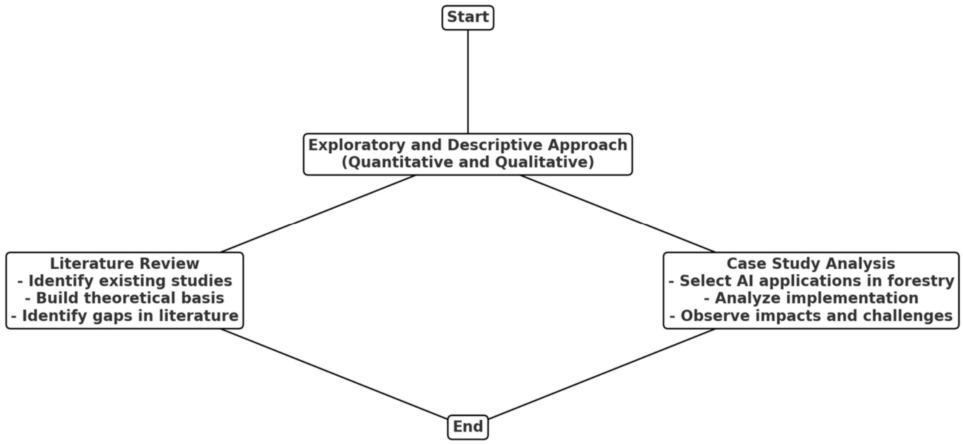

Figure 2. Methodological framework of this study.

Two sets of keywords were combined for the search: (1) terms related to AI, including "Artificial Intelligence", "Machine Learning", "Deep Learning", "Natural Language Processing", "Artificial Neural Networks", "Computer Vision", and "Expert Systems", to capture the diversity of AI technologies; and (2) terms related to forestry logistics, such as "Forestry Logistics", "Forest Supply Chain", "Timber Transportation", "Inventory Management", and "Forest Monitoring". Examples of combinations include "Artificial Intelligence AND Forestry Logistics" and "Machine Learning AND Timber Transportation". The initial search yielded 237 articles (Scopus: 152; Web of Science: 60; IEEE Xplore: 25), which were reduced to 198 unique records after duplicate removal.

Inclusion criteria were as follows: (1) articles published in English, (2) a focus on AI applications in forestry logistics or related supply chains, and (3) availability of full text. Exclusion criteria eliminated studies addressing solely forest ecology without a logistics connection or those not peer-reviewed (e.g., technical reports). The selection process comprised three stages: (1) an initial screening of titles and abstracts, excluding 108 irrelevant articles; (2) a full-text review of the remaining 90 articles, discarding 10 due to insufficient empirical data or lack of focus; and (3) a final validation, resulting in 80 included studies. These studies were categorized by country of origin, application area (e.g., transport planning, inventory management), and AI technology type, enabling a structured synthesis of findings.

The case study analysis concentrated on two documented implementations—transport optimization in eucalyptus plantations and forest monitoring with drones—chosen for their relevance and availability of detailed outcomes. Qualitative data from these cases were assessed to complement the SLR with practical evidence. Figure 3 illustrates the search and selection process, ensuring transparency and reproducibility. This dual approach provides a comprehensive evaluation, integrating theoretical insights and real-world applications of AI technologies in forestry logistics.

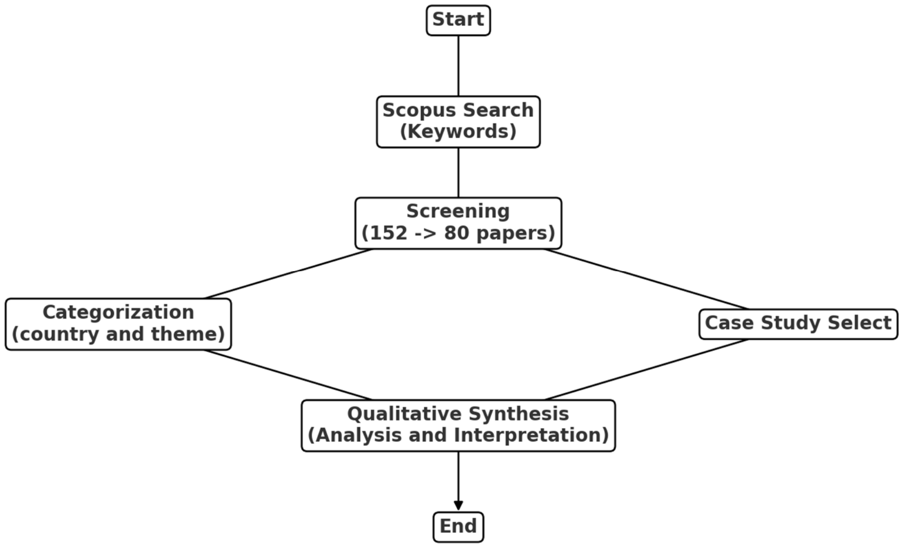

Figure 3. Enhanced workflow of the literature review and case study analysis, detailing the selection process from 237 initial articles to 80 final studies.

In the SLR, the search was performed across Scopus, Web of Science, and IEEE Xplore, covering publications from 2010 to 2024 to capture recent advancements in AI technologies. The initial search employed keyword combinations such as "Artificial Intelligence AND Forestry Logistics", "Machine Learning AND Timber Transportation", and others outlined in Section 2.1, retrieving 237 articles (Scopus: 152; Web of Science: 60; IEEE Xplore: 25). Following duplicate removal using bibliographic management software, 198 unique records remained. Additional filters included language (English), publication type (peer-reviewed articles), and full-text access, excluding theses, technical reports, and unavailable studies.

The selection process followed three steps: (1) an initial screening of titles and abstracts, eliminating 108 articles addressing topics such as pure forest ecology or technologies unrelated to logistics (e.g., plant genomics); (2) a full-text review of the remaining 90 articles, excluding 10 due to lack of empirical data (e.g., narrative reviews without quantitative results) or insufficient focus on forestry logistics; and (3) a final validation, confirming the 80 included studies based on their direct relevance to the study's objectives—exploring AI applications in transport, inventory management, and forest monitoring.

The final sample of 80 articles was selected for its balanced coverage of AI applications in forestry logistics, emphasizing both practical and theoretical evidence. These studies underwent qualitative analysis through thematic coding (e.g., transport, sustainability), ensuring alignment with research objectives and enabling external validation of the process.

2.2. Limitations of the Methodology

Although the methodology adopted was designed to provide a comprehensive analysis, it has some limitations that deserve consideration. One of the main limitations is the limited availability of detailed and specific data from the forestry sector, which may restrict the representativeness and depth of the analyses performed. In addition, the methodological approach relies on emerging technologies, which are not always widely available or accessible to all organizations, particularly in regions where technological resources are scarcer. Another potential limitation is the existence of biased results due to the use of data that may not fully reflect the diversity and complexity of the forestry operations analyzed.

Beyond keyword combinations, the retrieval strategy could be enhanced with citation tracking and related author searches to broaden the literature sample. However, time and resource constraints limited this study to keyword-based searches across Scopus, Web of Science, and IEEE Xplore. This approach, while robust, may miss fringe studies not indexed under selected terms, a limitation offset by the databases' comprehensive coverage of peer-reviewed work.

To address these limitations, future studies could leverage public data repositories or satellite imagery to supplement scarce forestry-specific data, while phased technology adoption (e.g., starting with low-cost sensors) could mitigate accessibility issues in resource-limited regions. Standardizing data collection protocols across studies could also reduce bias, enhancing representativeness.

3. Literature Review

3.1. Fundamental Concepts of the Forest Production Chain and Logistics

The forestry supply chain is a complex system that ranges from primary production, involving the cultivation and maintenance of forests, to the transformation and distribution of derived products, such as wood, paper, and biomass. This sector plays a strategic role in several economies, including Portugal, where it contributes significantly to exports and the country's economic and environmental sustainability. However, the logistics management of this chain faces specific challenges, such as the variability of forest resources, the geographical dispersion of plantations, and the high dependence on climatic and biological factors [20].

Forest logistics encompass critical processes, including transportation planning, inventory management, storage, and distribution of finished products. These processes are particularly influenced by the heterogeneity of forest resources, the need to preserve the quality of materials during transportation, and the complexity of integrating operations between rural and urban areas [21]. Lack of homogeneity in raw materials and challenging transportation and storage conditions further complicate logistical coordination and efficiency.

Logistics efficiency is therefore important to ensure the competitiveness of the sector while minimizing the associated environmental impacts. Studies such as that of D'Amours and Rönnqvist [22] highlight that the use of advanced planning models, supported by emerging technologies, can significantly improve the integration and management of the forestry value chain, addressing current limitations and preparing the sector for future challenges.

3.2. Applications of AI in Logistics

The ability to process large volumes of data, learn from historical patterns, and generate real-time forecasts allows AI to tackle complex problems more effectively than traditional approaches [23]. In logistics, AI applications can be grouped into three main categories:

1. Forecasting and Planning: AI is widely used to predict demand and supply, based on historical data and external variables such as weather conditions and market fluctuations [24]. In the forestry sector, this capability can be applied to predict tree growth, optimize felling cycles, and calculate transport requirements, reducing waste and operational costs [25].
2. Process Automation: AI tools have been employed to automate repetitive tasks such as inventory management and transport route planning [26]. These solutions not only increase efficiency but also reduce human error and enable more effective resource allocation [27].
3. Real-time Optimization: AI algorithms can be used to monitor and adjust logistics operations in real time, based on up-to-date data [28]. For example, sensors and IoT (Internet of Things)—a network of interconnected devices collecting and exchanging data—installed in vehicles and warehouses enable tracking of goods, monitoring of

transport conditions (e.g., temperature, humidity), and rapid responses to unexpected changes, enhancing operational agility [29].

These applications are increasingly being explored in the forestry sector, where, for example, Machine Learning algorithms are being used to plan transport routes that minimize costs and carbon emissions, while AI-based systems allow forests to be managed more sustainably, analyzing data from satellite and drone images to monitor the condition of plantations and prevent fires [30–33].

While not directly applicable to forestry, recent studies like Lu et al. [34] on crowdsourcing door-to-door delivery in Beijing highlight AI's role in optimizing last-mile logistics, offering insights into real-time route adjustments and cost efficiency that could inspire adaptive transport models in forestry supply chains.

3.3. Relevant AI Technologies and Tools

The forestry supply chain encompasses several distinct stages, each presenting unique logistical challenges. Primary production involves forest cultivation, including planting, maintenance, and harvesting, where geographical dispersion and biological variability complicate planning [35]. Processing transforms raw timber into products like lumber, pulp, or biomass, requiring efficient material flow and quality control amidst heterogeneous inputs. Distribution and transportation link these stages to markets, involving complex route planning and storage to preserve product integrity across rural and urban interfaces. Finally, end-use and waste management address product delivery and residue utilization, critical for sustainability. These stages, interdependent yet diverse, underscore the need for adaptive logistics solutions, which AI aims to enhance.

An example is the use of predictive analysis technologies in conjunction with computer simulation systems, which allow the modeling of logistics scenarios, assessing the impact of external variables, such as climate change, and testing solutions in virtual environments before their practical implementation [36,37]. This approach reduces the risks and costs associated with direct field experimentation while providing valuable insights into the effectiveness of planned strategies. On the other hand, cloud computing-based management systems allow the integration of data from multiple sources and real-time accessibility by different stakeholders [38]. This centralization and democratization of access to data improve coordination between the various links in the value chain, ensuring greater operational fluidity.

Another technology that has been transforming forestry logistics is Explainable Artificial Intelligence (XAI) [39]. Unlike traditional AI models, which often function as "black boxes", XAI systems offer greater transparency into their operations, allowing users to understand the decisions made by the algorithms [40]. This feature is particularly useful in the forestry sector, where the implementation of technological solutions requires strong trust on the part of managers and operational teams.

The advancement of edge computing technologies opens up new possibilities for operations in remote locations, a common reality in the forestry sector [41]. With these tools, data can be processed locally, directly on devices installed in the forests, such as IoT sensors or drones, reducing the dependence on continuous connectivity with central servers [42]. This decentralized processing capacity allows for faster and more efficient monitoring, even in areas that are difficult to access.

The incorporation of emerging technologies, including geospatial intelligence and blockchain analytics for traceability, has significantly influenced the forestry industry's capacity to tackle modern challenges and progress towards a more efficient and sustainable future. He and Turner [20] highlight how these technologies, in combination with other Industry 4.0 solutions, such as IoT and RFID, have the potential to optimize forestry supply chains, promoting greater efficiency and transparency. Bastos et al. [43] further emphasize that digitalization and the use of blockchain in forest biomass chains improve traceability and ensure more sustainable practices throughout the logistics chain. Also, Henriques and Westerlund [44] explore how blockchain, integrated with IoT, can revolutionize forest management, enabling unsupervised monitoring and accurate tracking of forest resources. Elias [45] reinforced the role of blockchain when combined with GIS in enabling more efficient traceability and more sustainable management of timber transportation, representing a technological evolution and a true transformation in the way forestry logistics operations are planned and executed, creating a more transparent, efficient model aligned with global sustainability objectives.

To provide a clearer understanding of AI technologies applied in forestry logistics, this section has been expanded to compare the strengths and weaknesses of key AI analytical methods. Machine Learning (ML) excels in predictive analytics and pattern recognition, leveraging large datasets for tasks like demand forecasting and inventory optimization; however, it requires extensive, high-quality data, which can pose a limitation in data-scarce regions. Neural Networks, particularly Deep Learning (DL), offer a superior performance in processing unstructured data, such as images from drones for forest monitoring, but their computational complexity and 'black box' nature can hinder interpretability and practical adoption. Blockchain, while not a traditional AI method, enhances traceability and transparency in supply chains through secure, decentralized data management, though it faces scalability challenges and high energy costs. Natural Language Processing (NLP) supports the analysis of textual data, such as forestry reports, but its application in logistics is less direct and often supplementary. These distinctions highlight ML and DL as foundational for predictive and real-time optimization tasks, while blockchain complements AI by ensuring data integrity, each suited to specific logistics challenges.

3.4. Gaps and Opportunities in the Literature

Despite significant advances in the application of AI in the forestry sector, the literature still presents important gaps. Many studies focus on specific applications, such as the use of algorithms for forest monitoring or logistics optimization, but there is a lack of integrated approaches that consider all stages of the value chain. Buchelt et al. [46] highlight that, although the use of drones and AI has been well-explored in specific contexts, such as ecological management, the lack of integration between solutions limits the overall impact of technology in the sector. Also, Shivaprakash et al. [47] point out that the social and ethical impacts of AI implementation, particularly in rural communities dependent on the forestry sector, have received little attention.

Another significant challenge is the quality and accessibility of the data needed to feed AI systems. As indicated by Causevic et al. [48], focusing on global forest conservation, the variability of forest ecosystems and the geographical dispersion of operations make it difficult to collect consistent and representative data, limiting the effectiveness of predictive models and automated systems. Similarly, Shivaprakash et al. [47], studying India's forestry sector, note that the social and ethical impacts of AI, particularly in rural communities, remain underexplored, reflecting regional disparities in technological adoption.

On the other hand, there are promising opportunities to expand the use of AI in the forestry sector, as the increasing availability of technologies such as drones, IoT sensors, and satellite imagery facilitates the collection of large-scale and real-time data [46]. In addition, advances in Machine Learning and Deep Learning algorithms open up new possibilities for the analysis and interpretation of these data, enabling more precise and sustainable management of forestry operations [49]. The global pressure to adopt sustainable practices and reduce carbon emissions also drives the demand for innovative AI-based solutions, as highlighted by Chisika et al. [50].

The literature reveals critical gaps, such as the lack of holistic frameworks integrating AI along the entire forestry value chain, which could amplify its impact. Opportunities abound with the increasing accessibility of real-time data from IoT and satellite systems, enabling more precise predictive models. Future research could explore hybrid AI solutions combining Machine Learning and optimization algorithms to address these gaps, fostering a more interconnected and sustainable logistics ecosystem.

4. Results and Discussion

The results of this study are based on a systematic analysis of 80 peer-reviewed publications obtained from the Scopus, Web of Science, and IEEE Xplore databases, covering the period from 2010 to 2024. Table 1 presents the distribution of these studies by country, highlighting Europe (35%), North America (25%), and Asia (20%), with Portugal accounting for 8%, reflecting the relevance of its forestry sector.

Table 1. Distribution of studies by country.

Country/Region	Number of Studies	Percentage
Europe	28	35%
North America	20	25%
Asia	16	20%
Portugal	6	8%
Others	10	12%
Total	80	100%

The qualitative analysis was conducted through thematic coding, identifying transportation, inventory efficiency, and environmental sustainability as central themes, aligned with the research objectives. The inclusion of a diverse sample, encompassing technologies such as ML, DL, computer vision, and NLP, addresses the bias of previous studies that focused exclusively on ML, providing a more holistic view of AI's impact.

4.1. Impacts of AI on the Optimization of Logistics Processes

4.1.1. Transport Planning

The transport of timber and other forest products represents one of the most expensive components of the forestry sector, having a significant impact on the operational efficiency and environmental footprint of the sector [51]. Some studies show that the application of AI technologies in transport planning can contribute to improving logistics efficiency and reducing costs and associated emissions [52].

Optimization algorithms, such as those based on the modified A-Star method, have been explored for route planning, demonstrating significant improvements in the efficiency of logistics operations. For example, Veisi et al. [53] used this approach to optimize timber transport, prioritizing shorter and optimized routes in terms of energy cost and environmental impact. Similarly, the multi-agent systems analyzed by Araújo et al. [54] proved to be effective in planning transport activities, dynamically adjusting operations to factors such as road conditions and cargo volume, and increasing coordination between different stages of the supply chain.

Additionally, the combination of AI algorithms with IoT sensors has enabled advances in real-time monitoring of transport vehicles and cargo conditions, in turn enabling dynamic adjustments to routes, optimizing the use of resources, and reducing energy waste. Malladi and Sowlati [55] also highlighted the role of optimization models at the operational level, demonstrating how these technologies can increase transport efficiency.

4.1.2. Inventory Management

Inventory management in the forestry sector faces significant challenges, particularly regarding the deterioration of timber and other stored products over time. The application of predictive models based on Machine Learning has shown promise in addressing this problem. Recent studies, such as that of Sumarlin and Qosidah [56], highlighted how Machine Learning algorithms, including Neural Networks and random forests, can be used to optimize inventory management by predicting behavior patterns and reducing operational inefficiency.

In addition, advanced approaches, such as those described by Zhao et al. [57], indicate that the use of Machine Learning in the context of the biomass and forest supply chain can improve logistics efficiency and reduce waste in storage operations. These models analyze variables such as storage duration and environmental conditions, allowing for more accurate prediction of product condition and optimization of stock rotation. Another relevant application, discussed by Raihan [58], involves the use of predictive algorithms to adjust inventory levels to market needs. This dynamic adjustment allows for more efficient management, minimizing the costs associated with excessive or insufficient stocks.

4.1.3. Waste Reduction

Studies such as that of Ming et al. [59] highlight how tools based on Machine Learning and Neural Networks can be used to optimize resource management and minimize losses in industrial processes. These technologies have been particularly effective in identifying patterns that allow for more efficient operational adjustments, promoting material recovery and waste reduction.

Holzinger et al. [5] highlight the importance of integrating AI into forestry operations, namely through the automation and digitalization of processes such as wood quality assessment. These approaches allow for more accurate sorting of raw materials before felling, avoiding waste of resources by ensuring that each tree is used for the most appropriate application. Additionally, AI tools have been applied to industrial processing, optimizing cuts and maximizing the use of raw materials, as mentioned by Guo et al. [60], who analyze innovations in the reuse of forest biomass.

Another significant contribution of AI in reducing waste is its ability to predict and mitigate operational inefficiencies in real time. Hernandez et al. [61] explored how the application of intelligent algorithms in sustainable supply chains can generate economic and environmental benefits.

4.1.4. Environmental Sustainability

Wang et al. [49] highlighted how AI-based solutions have been integrated into the concept of “Climate-Smart Forestry”, which combines predictive modeling and monitoring to optimize harvesting cycles, ensuring sustainable management practices aligned with climate change adaptation and mitigation.

In addition, Mahmood et al. [62] explore the role of AI in forest monitoring, particularly in protecting biodiversity and managing risks such as fires and pests. The use of drones and satellite imagery, combined with Machine Learning algorithms, has allowed for early detection of problems, facilitating preventive interventions. These technologies offer greater accuracy in identifying environmental risks and contribute to reducing the economic impacts associated with forest loss and environmental degradation.

Holzinger et al. [5] highlight that the transition from traditional practices to sustainable, AI-centric models requires the implementation of human-centric systems capable of integrating large volumes of data and adapting to the dynamic conditions of the sector. This approach reinforces the capacity for real-time monitoring and improves forest resilience, ensuring practices that are more balanced between economic efficiency and environmental responsibility. On the other hand, Galaz et al. [63] point out that the global adoption of AI technologies in the forestry and agricultural sector plays a crucial role in managing systemic environmental risks, such as the impact of climate change and biodiversity loss.

4.2. Practical Examples and Case Studies

4.2.1. Transport Optimization in Eucalyptus Plantations

The application of optimization models in the transportation of wood from eucalyptus plantations has demonstrated a significant impact on logistical efficiency and the reduction in operational costs. A study by Hirigoyen et al. [64] in eucalyptus plantations in Uruguay exemplifies the effectiveness of optimization algorithms in transport management and harvest scheduling. The results demonstrated that optimized planning reduced transportation costs by approximately 15% and increased the net present value by 10%, while also lowering carbon emissions by 12% through efficient routing.

This study evaluated the impact of optimized planning on reducing costs associated with transportation and increasing the net present value of operations, highlighting the ability to integrate variables such as wood and carbon prices into the decision model. The results demonstrated that the use of optimization algorithms allows for more efficient planning of transport routes, contributing to minimizing logistics costs and maximizing the financial and environmental sustainability of forestry operations. Although the study was conducted in Uruguay, the optimization principles presented are broadly applicable to eucalyptus plantations in other contexts, including Portugal, where the forestry chain is a strategic sector.

4.2.2. Forest Monitoring with Drones and AI

The application of drones equipped with computer vision technologies has proven to be a promising tool for real-time monitoring of forests, particularly in the context of pest and disease management. As highlighted by Duarte et al. [65], the use of systems based on data obtained by unmanned aerial vehicles (UAVs) allows for the rapid identification and monitoring of the presence of insects and diseases in forest areas, integrating multispectral and visible analysis techniques to improve accuracy in early detection.

Analysis of data collected by drones facilitates faster and more targeted interventions, contributing to the reduction in damage caused by pests and the preservation of forest health. These technologies offer greater efficiency compared to traditional monitoring methods, allowing large areas to be covered in shorter periods of time and with lower operational costs. Furthermore, computer vision techniques integrated with AI algorithms enable detailed and automated analysis of captured images, increasing the effectiveness of threat detection and mitigation.

Although quantitative data on damage reduction vary depending on local conditions and the scale of application, the systematic study by Duarte et al. [65] demonstrates that the use of drones, in combination with AI technologies is a significant step forward in improving forest resilience and ensuring more sustainable management of forest resources.

4.3. Limitations of AI in the Forestry Context

AI in the forestry context of implementation faces structural challenges that go beyond the most obvious technical or economic barriers [66]. One of the main obstacles is the difficulty in establishing adequate infrastructure in rural and forested environments, where digital connectivity is often limited or non-existent [67]. Studies like that of Sovacool et al. [68] document job displacement risks in technology-intensive sectors, estimating a

20–30% reduction in manual roles, a trend applicable to forestry automation. Mitigation strategies include reskilling programs, such as Portugal's 'ForestTech' initiative, which trains workers in AI system management, and incentivizing hybrid roles blending traditional and tech skills to preserve employment.

This limitation compromises the collection of real-time data and the ability to integrate AI systems into collaborative networks that depend on consistent connectivity. The lack of sufficient historical data, or of inadequate quality, represents another challenge, as AI predictive models rely on large volumes of representative data to ensure their effectiveness and accuracy [69].

In addition, the complexity of the forestry industry, which includes dynamic interactions between biological, social, and economic aspects, creates difficulties in translating these variables into measurable and usable data for AI systems [70]. For example, environmental variables, such as climate change and ecological disruptions, are often unpredictable and difficult to model, limiting the ability of algorithms to learn and respond appropriately to these fluctuations [71]. This limitation highlights the need for robust adaptive systems, which, although promising, are not yet widely available or developed for this specific context.

The training and technical capacity of teams responsible for forest management also presents a significant obstacle [72]. The introduction of advanced technological solutions requires specialized technical knowledge and the transformation of organizational and cultural practices rooted in traditional approaches [73]. Resistance to change, often associated with a lack of knowledge about the potential and benefits of AI, can inhibit enthusiasm for adopting new technologies [66]. This factor is particularly evident in regions where the forestry sector has historical and cultural economic importance but where management models remain essentially conventional [74].

A critical consideration in pursuing AI-driven efficiency is the potential trade-off with robustness. High efficiency, such as just-in-time inventory systems, can reduce costs but may leave operations vulnerable to disruptions, as seen during the COVID-19 pandemic when supply chain perturbations exposed the fragility of lean models. In forestry logistics, over-optimization could similarly compromise resilience to climate variability or market shifts. Balancing efficiency with adaptability—e.g., maintaining strategic reserves or flexible routing—could ensure sustainable operations, a factor warranting further exploration in AI implementation strategies.

Finally, the introduction of AI in the forestry sector also raises ethical and social concerns, especially in relation to the automation of processes and the potential replacement of jobs [63]. In rural communities that rely heavily on the forestry sector, the replacement of human labor by automated systems can exacerbate already existing socioeconomic inequalities, intensifying social challenges in these regions [68]. To ensure that AI implementation is beneficial and sustainable, it will be necessary to adopt inclusive strategies that involve redistributing employment opportunities and promoting reskilling programs [75]. These actions can help mitigate the negative impacts of automation, ensuring that technological evolution is accompanied by social progress.

4.4. Future Perspectives and Opportunities

Future prospects for the application of AI in the forestry sector point to a continuous and dynamic evolution, driven by the need to innovate in the face of growing challenges in sustainability, efficiency, and global competitiveness [76]. The integration of AI with other emerging technologies presents a central opportunity to transform the sector [77]. This technological convergence expands the individual capabilities of each solution and creates synergies that allow complex problems to be tackled more effectively. For example, the combination of IoT sensors with AI algorithms and blockchain-based platforms can increase traceability and transparency along the value chain, fostering trust between stakeholders and facilitating the certification of sustainable practices [78].

The creation of adaptive systems is another promising development, enabling AI-based solutions to respond in real time to unexpected changes, such as variations in weather conditions or abrupt changes in market demand [79]. Such systems, equipped with continuous learning capabilities, could automatically adjust transport, inventory, and harvesting plans, ensuring greater resilience and reducing the impact of disruptive events [79]. Adaptability will be especially important in a sector that is so dependent on external factors, where environmental and economic uncertainties play a major role [80].

An emerging opportunity lies in federated learning, a technique where AI models are collaboratively trained across multiple organizations without sharing proprietary data. Already practiced in other sectors, such as healthcare and finance, federated learning could enable forestry companies to enhance predictive models while preserving competitive advantages, offering a practical alternative to traditional data-sharing challenges.

Additionally, data sharing between organizations, facilitated by collaborative networks and digital platforms, could revolutionize the quality and usefulness of predictive models applied to forestry logistics [25]. This type of collaboration has the potential to mitigate limitations related to the scarcity of representative data, promoting a broader and more diverse base to feed AI systems. The adoption of common standards and interoperability protocols will facilitate these collaborations and maximize collective benefits.

Finally, the growing demand for environmentally responsible practices and the pressure of public policies focused on sustainability are factors that will drive the application of innovative solutions [81]. The technological evolution of the forestry industry, supported by AI, could become an example of how digital transformation can be aligned with sustainable development goals, positioning the sector as a global reference in efficiency, social responsibility, and environmental preservation [82].

5. Conclusions

AI is transforming forestry logistics, offering innovative solutions to complex challenges. The results of this study show that technologies such as Machine Learning algorithms, optimization systems, and IoT sensors enable significant gains in operational efficiency, environmental sustainability, and logistics resilience. Practical examples, such as the optimization of transport routes and forest monitoring with drones, have demonstrated notable reductions in costs, carbon emissions, and waste. Despite the advantages, the implementation of AI faces barriers such as the collection of quality data, initial adoption costs, and resistance to change from organizations and communities. These limitations highlight the importance of strategic partnerships between companies, government, and academic institutions to foster training, innovation, and data sharing in the sector. Looking forward, the integration of AI with emerging technologies, such as blockchain and adaptive analytics systems, represents a crucial opportunity to expand the benefits. This study reinforces that the responsible and inclusive adoption of AI is essential to ensure that digital transformation simultaneously contributes to the economic competitiveness and environmental preservation of the forestry sector. Policymakers should incentivize AI adoption through subsidies for small forestry firms, establish data-sharing consortia to improve model accuracy, and fund reskilling programs to offset automation's social impacts, ensuring industry-wide sustainability and equity. This study lays a foundation for future research by providing a replicable methodology and highlighting underexplored areas, such as the integration of federated learning and resilience-focused AI models. Researchers are encouraged to build on these findings, developing longitudinal studies and cross-sector comparisons to further refine AI's role in sustainable forestry logistics.

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