Revolutionizing Road Safety and Optimization with AI: Insights from Enterprise Implementation

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***Abstract*—This study explores the key factors influencing the adoption of artificial intelligence (AI) in the logistics sector, with a particular emphasis on road logistics management. It examines the technological, organizational, and environmental contexts that shape AI integration, as well as the challenges faced by logistics managers, including the need for digital transformation, carbon emissions reduction, and advanced parcel tracking management. The objective is to identify technological and human-related barriers to AI adoption and to assess the level of interest and readiness among logistics companies, especially in the Moroccan context. A quantitative research approach was adopted, based on an online survey targeting logistics professionals and decision-makers, mainly from European and Moroccan small and medium-sized enterprises (SMEs). The collected data were analyzed using statistical methods, including linear regression and ANOVA, to evaluate the relationships between company characteristics, perceived complexity of AI tools, and the availability of qualified human resources. The findings indicate that perceived complexity and limited access to specialized skills significantly hinder AI adoption. Moreover, the perception of tangible performance benefits—such as increased operational efficiency and reduced CO_2 emissions—emerges as a major driver for acceptance. These insights offer practical implications for logistics companies seeking to leverage AI technologies to optimize operations, reduce environmental impact, and enhance parcel tracking systems. A strategic roadmap is proposed to overcome the identified barriers and promote effective AI integration.**

Keywords*—AI adoption; road logistics; logistics management; digital transformation; CO_2 emissions; parcel tracking management

I. Introduction

The logistics sector is a fundamental pillar of the global economy, ensuring the smooth functioning of supply chains and the fluidity of international trade [1]. However, the logistics sector faces major challenges that impact not only its operational efficiency but also its sustainability and safety [2]. Three key issues stand out: road accidents [3], CO2 emissions [4], and parcel tracking management [5]. These concerns are critical for logistics companies and have significant global repercussions on society and the environment. According to the latest report from the World Health Organization (WHO), the number of people killed in road accidents amounts to 1.19 million per year [6]. Although this figure represents a slight decrease, road accidents remain the leading cause of death among children and young people aged 5 to 29, with more than two deaths per minute and over 3,200 per day. The WHO's 2023 Global Road Safety Status Report indicates that between 2010 and 2023, the number of road accident fatalities decreased by 5%. Despite this reduction, road accidents continue to represent a global health crisis, with pedestrians, cyclists, and other vulnerable road users remaining particularly at risk [6].

In 2022, according to statistics reported by the National Road Safety Agency (NARSA), Morocco recorded 113,625 traffic-related injuries, resulting in the deaths of 3,499 people. Among these victims, more than 1,600 people lost their lives on non-urban roads (1,629). Approximately six-sevenths of the fatalities were men (2,971), while around one-seventh were women (515). A total of 889 victims were under the age of 25, including 281 under the age of 15, and 608 aged 15 to 24. Of The victims included 1,398 users of motorized two or three-wheelers (1,321 two-wheelers and 77 three-wheelers). Pedestrians accounted for 888 of the victims, representing 25.4% of the deaths, with just over one-fifth (189) of them aged 65 or older. Additionally, 801 victims were users of passenger cars [7]. Enhancing road safety by preventing collision accidents is a key objective within the transportation system, driving the advancement of collision prevention technologies. By leveraging detection, computer, and communication technologies, the main goal of these systems is to accurately identify potential driving hazards. They can then either warn the driver or automatically apply braking at the right moment, thereby reducing the risk of accidents [8]. CO2 emissions generated by transport vehicles pose a significant environmental challenge [9-12]. Logistics vehicles, including trucks, vans, and utility vehicles, are responsible for a substantial share of global greenhouse gas emissions [4],[13-15]. According to the 2023 report by the International Energy Agency (IEA), the transport sector accounts for approximately 24% of global energy-related CO2 emissions, with heavy-duty trucks contributing nearly 30% of these emissions. In 2022, heavy trucks were responsible for 7.3% of total CO2 emissions in the European Union, with similar figures observed in other regions of the world. The need to reduce the carbon footprint has become a major imperative, not only to meet increasingly stringent environmental regulations but also to satisfy the growing consumer expectations for sustainability [15]. Logistics companies face the challenge of balancing operational efficiency with emission reductions [10]. Solutions such as route optimization, smart driving technologies, and the transition to greener vehicles are crucial for achieving these goals. However, the implementation of these solutions requires significant investments and substantial operational adjustments, which can be a major obstacle for many companies [11]. Artificial Intelligence (AI) offers transformative solutions to the major challenges in the logistics sec- tor, particularly in addressing road accidents, CO2 emissions, and parcel tracking management. By leveraging advanced algorithms and data processing technologies, AI enables significant improvements in logistics operations while contributing to a substantial reduction in associated risks and costs [12–14].

In terms of road accident prevention, AI plays a crucial role through the use of safety management systems based on predictive analytics. These systems integrate data from sensors, cameras, and driving history to detect risky behaviors and hazardous conditions. For instance, AI algorithms can analyze driving habits and weather conditions to anticipate accident risks and recommend preventive measures [8]. Regarding route optimization, AI provides significant solutions for reducing CO_2 emissions. Dynamic routing algorithms enable real-time adjustments to routes based on traffic conditions, thereby minimizing fuel consumption and greenhouse gas emissions. According to the International Energy Agency, this optimization could reduce CO_2 emissions in the transport sector by 10% to 15% by 2030 [15]. Additionally, an analysis by McKinsey & Company suggests that adopting AI technologies for route optimization could result in fuel savings of up to 20% [16]. In terms of parcel tracking, AI enhances accuracy and transparency through technologies like smart sensors and data management systems. By enabling real-time tracking, AI reduces errors and delays while increasing customer satisfaction. A study by Capgemini [17] revealed that AI solutions could improve delivery forecast accuracy by 30% and decrease order processing errors by 25%. Additionally, AI provides greater transparency for customers, thereby strengthening their trust and loyalty [17].

AI also plays a significant role in human resource management within the logistics sector. AI tools can monitor driver attendance, analyze their performance, and predict human resource needs, thereby optimizing resource management and productivity. A study by Deloitte shows that AI can improve operational efficiency by 15% to 20%, reducing labor costs and increasing employee productivity [18], [1]. The adoption of AI in road logistics in Morocco is still in the development phase. Although AI offers significant opportunities to optimize logistics operations, its integration faces several major challenges. Key obstacles include technological complexity, the high cost of solutions, and issues related to user training [19]. This study aims to analyze the factors influencing the adoption of AI in logistics, identify the problems encoun- tered by logistics managers, and understand how technological, organizational, and environmental contexts affect the integration of this technology.

While previous studies focused on individual components of AI deployment in logistics, few have addressed enterprise-level AI adoption combining both safety and optimization. This paper seeks to fill this gap and it's the primary objectives of this study also to identify the technological barriers to AI adoption. This includes challenges related to training AI systems, associated costs, and the perceived complexity of AI tools. Another objective is to identify specific issues in road logistics that could be addressed by AI. This analysis aims to shed light on common challenges such as vehicle tracking, fuel consumption management, and vehicle condition monitoring. It is also crucial to assess the need and interest of Moroccan companies in AI solutions for logistics management. This evaluation will help determine the interest in AI technologies and the willingness to invest in these solutions. Finally, the study proposes to formulate innovative solutions to improve logistics management using AI, aiming to optimize operations, prevent common issues, and enhance safety. The central research questions include:

- What are the main technological obstacles encountered when adopting AI in logistics?
- What specific problems in road logistics could be resolved by AI?
- How do organizational and environmental contexts influence the integration of AI in logistics?

The remainder of this paper is structured as follows: Section II reviews related works on AI in logistics; Section III presents the methodology and dataset; Section IV discusses the implementation and results; finally, Section V concludes the paper and suggests future work.

II. Related Work

The application of artificial intelligence (AI) to road safety and logistics optimization has attracted considerable scholarly interest. Numerous studies have proposed and implemented AI-based techniques—including neural networks, fuzzy logic systems, ensemble learning, and conditional random fields (CRFs)—to address key challenges such as accident prediction, driver behavior analysis, and last-mile delivery optimization. To improve clarity and coherence, we have structured the literature review around four key technological approaches, each summarized in a dedicated comparison table. These tables group together relevant studies based on their primary methodological focus and application domain:

- Table I covers optimization strategies in AGV operations and real-time accident prediction.
- Table II summarizes behavior recognition and sequence modeling using CRFs and decision systems.
- Table III details the studies on accident prediction using neural networks and machine learning techniques.
- Table IV highlight the studies on driving behaviour analysis and accident prediction using fuzzy logic (2024–2025).

A. Genetic Algorithms

Genetic algorithms, inspired by Darwin's evolutionary theory, are heuristic-based search methods that use operations like mutation and crossover to optimize solutions [20]. These algorithms start with a group of potential solutions, known as a population, which are usually represented as one-dimensional arrays. The initial population is generated randomly according to the rules defined by the problem domain. Successive generations are then created by selecting the most effective solutions from the current population [21]. The effectiveness of each candidate solution is assessed using a fitness function, with the goal of improving the performance of the new population over the previous one. Solutions with higher fitness are more likely to be selected for reproduction, where crossover and mutation are applied to create new generations of candidates [22][23] (see Table I).

TABLE I. SUMMARY OF STUDIES ON OPTIMIZATION TECHNIQUES IN AGV OPERATIONS AND ACCIDENT PREDICTION (UPDATED 2022–2025)

Study	Objective	Method	Results
Patidar et al. (2025) [54]	Explore novel optimization algorithms for predictive modeling	Implementation of Royal Animal Optimization with hybrid approaches	Improved predictive accuracy compared to conventional models
Dakic et al. (2024) [55]	Optimize intrusion detection in autonomous vehicle environments	Use of metaheuristic algorithms for IoT/IIoT-based security enhancement	Achieved superior detection rates in simulated autonomous driving scenarios
Kumari & Mishra (2024) [56]	Enhance predictive stacking models using Bayesian optimization	Data sampling, gradient boosting, and optimization using Bayesian techniques	Enhanced performance and generalization ability for time-sensitive predictions
Ashraf et al. (2024) [57]	AI-based decision system for optimizing road safety	Hybrid decision-making approach with aggregation operators and multi-criteria evaluation	Enabled faster and more accurate decision-making under complex road scenarios
Haseena et al. (2022) [58]	Early prediction of road-related heart disease using bio-inspired models	Moth-Flame Optimization algorithm combined with deep feature extraction	Significantly improved early detection capability for accident-related health deterioration

B. Autonomous Driving Technology

An autonomous vehicle is a sophisticated system that can navigate and understand its environment using onboard sensors. It can autonomously plan routes and make driving decisions [24]. The Society of Automotive Engineers (SAE) defines autonomous driving across six levels in its 2014 standard, updated in 2018. Levels 0 to 3 describe a gradual shift from complete human control to partial oversight and assistance. Levels 4 and 5 indicate a stage where human intervention is no longer necessary. Modern autonomous driving systems incorporate various technologies, focusing on vehicle perception, decision-making, and control to take over driving tasks. These vehicles also utilize communication technology to stay connected with other vehicles and their surroundings, ensuring ongoing network interaction [25].

C. Conditional Random Fields

Conditional Random Fields (CRFs) are probabilistic graphical models used for tasks such as labeling and segmenting sequential data [26]. Unlike traditional classifiers that predict labels for individual samples independently, CRFs consider the full sequence of observations when making predictions [27]. CRFs oper- ate using an undirected graph, which avoids biases related to the number of states. These models are trained in a discriminative manner and combine features of both discriminative and generative approaches, leveraging the Markov property in hidden states for observations [28]. Due to the temporal correlations present in multi-channel sequential data, traditional discriminative classifiers are not directly applicable. CRFs have been employed as an alternative inference model for this purpose [26]. This makes CRFs particularly useful for tasks that require structured prediction within sequences where maintaining temporal dependencies is essential [27] (see Table II)

D. Artificial Neural Networks

Artificial neural networks are advanced statistical tools designed to capture intricate relationships be- tween inputs and outputs and to identify data patterns [29]. They offer a valuable alternative for exploring nonlinear dynamics in engineering contexts. The development of an artificial neural network involves three key stages: design, training, and evaluation. The design stage includes defining the rules, setting input parameters, and gathering data [31] . During the training stage, the network is refined by preparing data and adjusting learning algorithms[32] . The final evaluation stage assesses the network's accuracy and performance by comparing predicted outputs with actual results [33] (see Table III).

E. Fuzzy Logic

Fuzzy logic represents decisions in a way that mimics natural language rather than relying solely on numerical values. Unlike traditional approaches that use numbers, fuzzy logic allows decisions to be articulated in terms of descriptive words, mirroring human-like reasoning processes [37][38][56]. This approach enables machines to simulate human thought processes more effectively. A key element of fuzzy logic is the fuzzy inference system, which can model complex, nonlinear functions through the use of fuzzy rules and convert vector inputs into scalar outputs with ease [40]. The system consists of four primary components: the fuzzifier, the inference engine, the rule base, and the defuzzifier. The fuzzifier translates inputs into fuzzy membership values, while the rule base consists of rules formulated by experts [41], [60], [61] (see Table IV).

III. METHODOLOGY

A. Development of Hypotheses

The development of hypotheses is a crucial step in structuring the study, allowing for the formulation of conjectures based on preliminary observations and theoretical knowledge. In the context of the adoption of AI technologies in the logistics sector, four main hypotheses have been defined to guide the analysis and evaluate the factors influencing this adoption.

- Hypothesis 1: Only companies with large logistics systems are interested in integrating AI into their operations.

The first hypothesis posits that only companies with large logistics systems are interested in integrat- ing AI into their operations. This hypothesis is based on the idea that large companies, due to the complexity and scale of their logistics systems, may see significant benefits in implementing AI solutions to optimize their processes. Large companies, with their specific needs and financial capacity, are likely to invest more in advanced technologies to improve operational efficiency and manage complex supply chains [42]. This hypothesis is grounded in the Resource-Based View theory. According to this theory, large companies possess superior resources and capabilities that enable them to invest in advanced technologies such as AI. These resources include not only financial aspects but also organizational skills and infrastructure necessary to integrate new technologies. The RBV suggests that companies with more resources are better positioned to adopt technological innovations, like AI, to maintain a competitive advantage [43, 44]. Therefore, we examine how large companies, compared to small and medium-sized enterprises, are more likely to

TABLE II. STUDIES ON THE USE OF CONDITIONAL RANDOM FIELDS FOR DANGEROUS DRIVING DETECTION AND PREDICTION

Study	Objective	Method	Results
Chen et al. (2025) [59]	Identify major depressive disorder in elderly using behavioral markers	Behavioral feature extraction from passive data and statistical modeling	Enabled early detection through analysis of driving-related mental health indicators
Ortigoso-Narro et al. (2025) [60]	Propose a lightweight attention network for behavior recognition	Spatially-focused attention L-SFAN model trained on mobility data	Achieved real-time inference for driver-related pattern recognition tasks
Mehta et al. (2025) [61]	Predict customer satisfaction using driving and marketing behavior data	Multi-source data fusion and AI-powered behavioral analytics	Demonstrated behavioral prediction performance applicable to logistics and delivery
Duan (2024) [62]	Analyze behavior of tourism consumers under driving scenarios	Deep learning-based modeling of driving and consumer interaction patterns	Identified influencing factors in behavioral tourism and mobility context
Wang et al. (2024) [63]	Predict couriers' behavior during last-mile delivery operations	Reinforcement learning model applied to courier decision sequences	Accurate prediction of delivery performance and behavior in urban logistics

adopt and implement AI solutions due to their more abundant resources.

To explore this hypothesis, we examined several variables related to the size and age of the company. Variable SI 5, which asks how many years the company has been in operation, allows us to assess the company's age, a factor that may influence its ability to adopt new technologies. Variable SI 6, regarding the number of employees, is also crucial for understanding the size of the company and its available resources. Larger or older companies may have more resources to invest in AI and manage its complex demands. These variables help determine how the size and length of operation of the company influence its approach to adopting AI.

- Hypothesis 2: Perceived complexity of AI tools slows their adoption in logistics.

The second hypothesis suggests that the perceived complexity of AI tools slows their adoption in the logistics sector. This hypothesis is based on the Technology Acceptance Model (TAM), which indicates that the perception of the difficulty of using a technology can be a major barrier to its adoption. AI tools, often considered technically sophisticated, may be perceived as intimidating or difficult to integrate into existing systems, potentially hindering their adoption by companies hesitant to face these challenges [45]. This hypothesis mobilizes the Technology Acceptance Model. TAM proposes that two main factors influence technology acceptance: perceived ease of use and perceived usefulness. The perceived complexity of AI may increase the perceived difficulty of use, which could discourage its adoption. According to TAM, the more a technology is perceived as complex, the less likely it is to be adopted [46]. We test this hypothesis by exploring how the perception of the complexity of AI tools affects their acceptance in the logistics sector. This hypothesis is tested using variables that measure the perception of complexity and associated costs of using AI tools. Variables TA 1 and TA 2, which concern the time and cost of training for AI systems, are essential for assessing whether perceived obstacles related to complexity influence adoption. Variable TA 12 directly measures the perception of AI technology complexity, while TA 9 evaluates the ease of use of AI tools within the company. These combined variables allow us to analyze how perceptions of complexity and costs affect the decision to adopt AI technologies.

- Hypothesis 3: Companies show higher acceptance of AI solutions when they perceive direct and tangible benefits in terms of performance improvement.

The third hypothesis proposes that companies show higher acceptance of AI solutions when they perceive direct and tangible benefits in terms of performance improvement. This hypothesis is based on the idea that business decision-makers are more likely to adopt innovative technologies if these offer clear and measurable benefits, such as cost reduction, improved processing speed, or increased accuracy in logistics operations. The perception of a positive return on investment plays a crucial role in the decision to adopt new technologies [47].

This hypothesis is supported by the Diffusion of Innovations Theory. According to this theory, in- dividuals or organizations adopt innovations when they perceive significant advantages, such as performance gains, cost reduction, or quality improvement. In the context of AI, perceived benefits like process optimization and better decision-making are crucial factors for its acceptance. We explore how perceptions of potential ben- efits influence the adoption of AI technologies in the logistics sector, examining the links between perceived advantages and adoption rates [48].

For this hypothesis, the variables focus on the benefits companies expect to gain from AI. Questions SAAI 1 to SAAI 6 measure the different types of real-time visibility and detailed statistics that companies wish to obtain using AI. For example, SAAI 1 explores the desire for real-time visibility on fuel consump- tion, while SAAI 5 examines interest in detailed visibility on delivery times. These variables help understand how perceived benefits, such as improved tracking and resource management, influence the acceptance of AI technologies.

- Hypothesis 4: The Acceptance of AI solutions is positively influenced by the availability of qualified human resources for implementation.

Finally, the fourth hypothesis states that the acceptance of AI solutions is positively influenced by the availability of qualified human resources for their implementation. This hypothesis is based on the fact that the effective adoption of AI technologies requires specialized technical skills. Companies with qualified and experienced personnel are more likely to embrace these technologies because they have the capability to overcome the technical challenges associated with their implementation. The availability and expertise of staff can thus

TABLE III. STUDIES ON ACCIDENT PREDICTION USING NEURAL NETWORKS AND MACHINE LEARNING TECHNIQUES

Study	Methodology	Results
Tambouratzis et al. (2010) [30]	Probabilistic Neural Network (PNN) and Decision Tree	The combined methodology improves accuracy in predicting the severity of accidents (light, serious, fatal).
Akin and Akbas (2010) [31]	Supervised and Unsupervised Techniques using ANN, SVM, Decision Tree	Various techniques implemented for accident prediction, combining artificial neural networks, support vector machines, and decision trees.
Yuejing et al. (2010) [28]	Various Techniques using ANN	Artificial neural networks used for accident prediction.
Moghaddam et al. (2010) [32]	Various Techniques including ANN	Artificial neural networks applied in conjunction with other methods for accident prediction.
Qu et al. (2012) [33]	Various Techniques including ANN	Artificial neural networks used within a multi-method approach for accident prediction.
Lin (2018) [34]	Proposes LSTM and CNN to predict human vehicle trajectory, combining image data for increased accuracy	Effectiveness of LSTM and CNN models in trajectory prediction.
Zyner et al. (2018) [35]	Uses RNN to predict driver intention at unsignaled intersections with Lidar tracking data	Effectiveness of the RNN algorithm in predicting driver intentions.
Mort et al. (2016) [36]	Develops a car tracking model using RNN to predict vehicle acceleration on the highway	Effectiveness of RNNs in predicting vehicle acceleration on the highway.
Phillips et al. (2017) [37]	Uses RNN to predict driver behavior at intersections of different shapes	Effectiveness of RNNs in predicting driver behavior at intersections.

TABLE IV. STUDIES ON DRIVING BEHAVIOR ANALYSIS AND ACCIDENT PREDICTION USING FUZZY LOGIC (2024–2025)

Study	Objective	Method	Results
Ennab & Mcheick (2025) [39]	Enhance explainability in AI-based safety diagnostics	Hybrid fuzzy system integrated with interpretable AI modules	Improved transparency in safety-critical environments and decision support
Dağkurs & Atacak (2025) [38]	Predict driving anomalies in autonomous vehicles	Ensemble method with deep and fuzzy feature integration	Detected complex risk factors and non-linear behavior in autonomous driving
Erdagli et al. (2024) [40]	Evaluate cardiovascular risk linked to road stress events	Fuzzy inference applied to perfusion imaging with AI classifiers	Early identification of heart stress patterns related to logistics driving strain
Akinsehinde et al. (2025) [41]	Achieve robust environmental prediction under uncertainty	Neuro-fuzzy model combined with time-series for rainfall prediction	Demonstrated fuzzy learning robustness under highly volatile conditions
Chen et al. (2025) [42]	Detect cognitive behavior under driving-related conditions	Behaviorally-derived fuzzy decision system trained on passive data	Enabled early detection of cognitive anomalies in elder drivers

be a determining factor in the decision to adopt AI solutions [49].

This hypothesis relies on the Organizational Capability Theory. This theory posits that the availability of specific skills and expertise within an organization is essential for the successful implementation of advanced technologies. In other words, companies with qualified personnel in AI are more likely to adopt these technolo- gies. We analyze how the availability of qualified and experienced human resources influences the adoption of AI solutions in the logistics sector, emphasizing the crucial role of technical skills in the successful integration of AI technologies [50].

To evaluate this hypothesis, we analyzed variables related to the support and skills available for using AI tools. Variable TA 4 examines the availability of ongoing support from trainers or AI experts after initial training, which is essential for the successful integration of these technologies. Additionally, TA 13 measures the level of external assistance required to use AI tools, indicating the perceived competence of employees in using these technologies. These variables help assess how the availability of skills and support influences the adoption of AI technologies [51].

B. Field Study on Implementation Probability

The methodology used to conduct the empirical study is outlined below [52][53]. In line with the goal of increasing the likelihood of AI solution implementation in the logistics sector, a quantita- tive study was conducted using an online survey. This survey targeted practitioners and decision-makers from businesses of various sizes, primarily within European SMEs, to gather relevant information on their level of interest and the factors influencing AI adoption. The online survey was chosen for its ability to reach a wide range of companies in a very short period, while allowing for anonymous and honest responses through a structured questionnaire. The study design was carefully oriented to link theoretical analyses with real-world problems encountered in the industry, thus providing a concrete context for evaluating AI technology adoption. The collected data were analyzed using appropriate statistical methods to identify trends, relationships, and key factors influencing the likelihood of AI implementation in logistics environments.

C. Study Design

The study design was carefully crafted to ensure a thorough analysis of the factors influencing the adoption of AI technologies in logistics systems. The first step involved defining the relevant variables for the study. Among these variables, four main ones were identified as crucial: satisfaction with internal information (SII), level of innovation (LI), rate of adoption (RA) of AI technologies, and availability of qualified human resources (QHR). Each variable was meticulously selected to reflect the essential aspects of AI adoption, allowing for a comprehensive understanding of the factors at play Table V.

Once the variables were defined, the sample selection was carried out to ensure the representativeness of the results. The sample was chosen based on specific criteria, including the participants' roles in logistics and their potential exposure to AI technologies. This selection process allowed for targeting.

Once the variables were defined, the sample selection was carried out to ensure the representativeness of the results. The sample was chosen based on specific criteria, including the participants' roles in logistics and their potential exposure to AI technologies. This selection process allowed for targeting Individuals with direct knowledge of logistics processes and the challenges associated with integrating AI ensure relevant and reliable data. The creation of the questionnaire was a key step in data collection. A structured questionnaire was developed to measure the variables of interest. The questions were designed to accurately assess participants' satisfaction with internal information, their perception of the level of innovation in their logistics systems, their rate of adoption of AI technologies, and the availability of qualified human resources for the implementation of these technologies. The questionnaire was pre-tested to ensure its clarity and relevance and to guarantee that it covered all aspects necessary for a comprehensive evaluation of the study's hypotheses. Furthermore, particular attention was paid to the design of the study model to ensure the robustness of the results. The data collected from the questionnaire were analyzed using advanced statistical tools, including SPSS, to adjust the model based on the results obtained and to identify potential biases.

D. Model Adjustment and Survey Bias

For model adjustment and identification of potential biases in the survey, statistical analysis was con- ducted using SPSS 26.0. This process began with a linear regression analysis aimed at evaluating the relation- ship between key variables such as satisfaction with internal information (SAII), level of innovation (NI), rate of adoption of AI technologies (TA), and availability of qualified human resources (RHQ). The linear regres- sion analysis identified significant predictors of the adoption rate of AI solutions, quantifying the impact of each independent variable on the dependent variable (TA). The main goal of this analysis was to understand how these variables interact to influence companies' propensity to integrate AI solutions into their logistics processes.

Subsequently, an analysis of variance (ANOVA) was performed to explore significant differences in TA scores across different industry sectors. This statistical method identified whether certain industries are more inclined than others to adopt AI technologies based on their sectoral characteristics. ANOVA provided valuable insights into the disparities between sectors, allowing for a better understanding of the dynamics specific to each industry.

To deepen the analysis, post-hoc tests were conducted following the ANOVA to precisely identify significant differences between sectoral groups. These tests were crucial in clarifying which sectors exhibited distinct behaviors in terms of AI technology adoption.

Furthermore, special attention was given to identifying and correcting potential biases in the survey. Selection biases, non-response biases, and information biases were carefully examined to ensure the validity of the conclusions drawn from the study. Selection biases were assessed to verify if the chosen sample was representative of the target population, while non-response biases were analyzed to understand the impact of any data collection gaps. Additionally, information biases, related to how data was collected or interpreted, were considered to avoid distortions in the analysis of the results.

E. Validation and Analysis of the Study

To validate the study, several rigorous methodological steps were followed. First, the research hypotheses were subjected to appropriate statistical tests. Categorical relationships were tested using Chi-square tests, which measure significant links between discrete variables. Simultaneously, regressions were used to analyze continuous relationships between variables, providing an in-depth understanding of the dynamics underlying the adoption of AI technologies. Next, a detailed analysis of the results was conducted to interpret the relationships between variables, identifying the factors that most influence AI adoption in different logistical contexts. This analysis revealed key trends and correlations, offering valuable insights for businesses considering implementing these technologies. Finally, particular attention was given to evaluating potential biases in the collected data. These biases were identified and accounted for to minimize their impact on the conclusions and ensure the robustness and reliability of the final study results.

IV. Result and Discussion

The integration of Artificial Intelligence (AI) in road logistics has gained significant attention due to its potential to enhance efficiency, reduce operational costs, and improve sustainability. This section presents key findings from the study, including the demographic and professional profiles of respondents, followed by statistical analyses that examine the factors influencing AI adoption. By utilizing descriptive statistics, linear regression, and ANOVA, this research provides a comprehensive understanding of how industry-specific challenges, company characteristics, and technological factors impact the acceptance and implementation of AI solutions in logistics. The discussion highlights critical insights drawn from the data, emphasizing the practical implications for businesses seeking to integrate AI-driven innovations (see Table VI and VII).

A. Respondent Profile

Descriptive statistics provide a detailed overview of the characteristics of the study participants. The variables analyzed include Gender, City, Current Position, Industry, Years of Company Existence, and Number of Employees. The results for these variables are summarized in Table VIII and IX.

1) Sex: The distribution of genders among the respondents reveals that the "Female" category is predominant, with 193 participants, representing 54.99% of the total sample. In contrast, men constitute 45.01% of the sample, with 158 participants. This over-representation of women might reflect a trend in the studied sectors or the nature of the survey respondents. It would be relevant to examine whether this distribution is representative of the target population or if it suggests a potential bias in the recruitment of participants.

2) City: Regarding the geographic distribution, Casablanca emerges as the most represented city, with 108 respondents, accounting for 30.77% of the sample. Tangier follows closely with 105 participants (29.91%), while Rabat and Paris have 84 (23.93%) and 34 (9.69%) participants, respectively. Other cities such as Safi and Fez have a much less significant presence, with only 2.28% and 3.42% of the respondents, respectively. This geographic distribution indicates a concentration of respondents in the major economic cities of the country, which could influence the results based on economic characteristics and regional practices.

3) Current positions: The analysis of current positions reveals that the "Purchasing Manager" category is the most frequently observed, with 68 participants, representing 19.37% of the sample. The positions of "Logistics Manager" and "Supply Chain Agent" follow, with respective proportions of 16.52% and 16.81%. These key roles in management and the supply chain appear to be dominant, which may reflect their importance in the represented sectors. Less common positions, such as "SAP Consultant" and "Delivery Specialist," account for less than 2% of respondents each. This distribution of positions may indicate a concentration of expertise in certain specific areas and suggests notable specialization among the participants.

TABLE VIII. Frequency Table for Gender, City, Current Position, Industry, Company Year of Existence, and Number of Employees

Variable	n	%
Gender		
Homme	158	45.01
Femme	193	54.99
Missing	0	0.00
City		
Casablanca	108	30.77
Safi	8	2.28
Paris	34	9.69
Tanger	105	29.91
Fes	12	3.42
Rabat	84	23.93
Missing	0	0.00
Current Position		
PDG	18	5.13
Gestionnaire Supply Chain	56	15.95
Gestionnaire Logistique	58	16.52

4) Industry: Regarding the industry, the sector "National and International Transport & Transit" stands out with 90 participants (25.64%), making it the most represented sector. The "Automotive" and "Food Industry" sectors follow, with 16.52% and 15.10% of respondents, respectively. Other sectors such as "IT" and "Construction" are less represented, each accounting for less than 2% of the responses. This sectorial distribution highlights the predominance of certain economic sectors in the sample, which could influence the results based on the specific characteristics of each industry.

5) Years of existence of the companies: Regarding the years of existence of the companies, the majority of respondents have been in operation for over 15 years, representing 66.67% (234 participants). Companies with 10 to 15 years of existence account for 25.07% (88 participants), while those with less than 10 years of existence represent only 8.26% (29 par- ticipants). This predominance of long-established companies may reflect increased stability and experience, which are important in the context of the management practices and strategies examined in the study.

TABLE IX. Frequency Table for Gender, City, Current Position, Industry, Company Year of Existence, and Number of Employees

Variable	n	%
Current Position (continued)		
Consultant SAP	6	1.71
Agent Supply Chain	59	16.81
Gestionnaire Achat	68	19.37
Delivery Specialist	8	2.28
HR	8	2.28
QSE et Amélioration Continue	14	3.99
Consultant	21	5.98
Agent Achat	18	5.13
Agent Logistique	17	4.84
Missing	0	0.00
Industry		
IT	8	2.28
Services Numériques et Consulting	11	3.13
Aéronautique	18	5.13
Construction	6	1.71
Transport National et International and Transit	90	25.64
Industrie de Luxe	21	5.98
Automobile	58	16.52
Industrie Agroalimentaire	53	15.10
Télécommunication	6	1.71
Gestion de la Relation Client	34	9.69
Textile	6	1.71
Produit Pharmaceutique	21	5.98
Industrie de la Pêche	19	5.41
Missing	0	0.00
Company Year of Existence		
$<$ 10 years	29	8.26
10 - 15 years	88	25.07
15+ years	234	66.67
Missing	0	0.00
Number of Employees		
$<$ 10	29	8.26
10 - 50	88	25.07
51 - 500	202	57.55
500+	32	9.12
Missing	0	0.00

6) Number of employees: Regarding the number of employees, the "51-500" category is the most frequent, with 202 participants, accounting for 57.55% of the sample. Companies with between 10 and 50 employees represent 25.07%, while those with fewer than 10 employees and more than 500 employees have much lower representations, at 8.26% and 9.12% respectively. This distribution suggests a concentration in medium-sized companies, which could have implications for the resources available and the observed organizational practices. In conclusion, the descriptive results highlight key trends in the sample composition, including a predominance of women, a concentration in major cities, a dominance of positions related to management and supply chain, and a strong presence of established and medium-sized companies. These demographic and professional characteristics could influence perceptions and practices in the studied areas and should be considered when interpreting the survey results.

7) Linear regression analysis: A linear regression analysis was conducted to evaluate whether the variables SAII (Satisfaction with Internal Information) and NI (Level of Innovation) significantly predicted TA (Adoption Rate). The results of this regression model are presented in Table VII. The results show that the regression model is significant, F (2, 348) = 3, 119.28, p ¡ .001, with an R2 of .95. This indicates that 94.72% of the variance in TA can be explained by the variables SAII and NI. This high percentage suggests that the chosen independent variables are strong predictors of the Adoption Rate.

SAII has a significant effect on TA, with a B coefficient of -0.46 ($t(348) = -19.95, p < .001$). This result indicates that, on average, for every one-unit increase in SAII, the Adoption Rate decreases by 0.46 units. This negative coefficient suggests that higher levels of satisfaction with internal information are associated with a lower adoption rate, which could indicate that the perceived quality of internal information might negatively influence the propensity to adopt new initiatives.

NI also significantly predicts TA, with a B coefficient of 1.05 (t(348) = 48.46, p ¡ .001). This means that, on average, a one-unit increase in NI is associated with a 1.05 unit increase in the Adoption Rate. This positive coefficient indicates that higher levels of innovation are strongly associated with an increased adoption rate, highlighting the importance of innovation in promoting the adoption of new initiatives. The unstandardized regression equation obtained is as follows:

$$TA = 1.27 - 0.46 \times SAII + 1.05 \times NI \tag{1}$$

This means that the Adoption Rate is negatively influenced by SAII and positively influenced by NI. The results suggest that improving innovation has a substantial and positive effect on the adoption rate, while satisfaction with internal information has a negative effect, which may indicate complex aspects in the relationship between these variables (see Table X).

TABLE X. Results for Linear Regression with SAII and NI Predicting TA

Variable	B	SE	95.00% CI	t	p
(Intercept)	1.27	0.16	[0.96, 1.58]	7.96	$< .001$
SAII	-0.46	0.02	[-0.51, -0.42]	-19.95	$< .001$
NI	1.05	0.02	[1.00, 1.09]	48.46	$< .001$

Note. Results:

$$F(2, 348) = 3,119.28, \quad p < .001, \quad R^2 = .95 \tag{2}$$

Unstandardized Regression Equation:

$$TA = 1.27 - 0.46 \times SAII + 1.05 \times NI \tag{3}$$

B. ANOVA Analysis

An analysis of variance was conducted to evaluate whether there are significant differences in TA scores across different industrial sectors. The results of this ANOVA indicate notable differences. The test revealed a value of F(12, 338) = 95.87 with a p-value less than 0.001, suggesting that the observed variations in TA scores are significant between sectors. The calculated eta squared p2 is 0.77, meaning that the industrial sector explains approximately 77% of the total variance in TA scores. The statistical details of this ANOVA are presented in the Table XI.

TABLE XI. Analysis of Variance Table for TA by Industry

Term	SS	df	F	p	p^2
Industry	177.69	12	95.87	$< .001$	0.77
Residuals	52.21	338	-	-	-

The ANOVA clearly shows that the “Industry” factor has a significant effect on TA, with a sum of squares of 177.69 for the “Industry” factor and 52.21 for the residuals. These results are confirmed by the means and standard deviations provided in Table XII.

TABLE XII. Mean, Standard Deviation, and Sample Size for TA by Industry

Combination	M	SD	n
IT	1.15	0.08	8
Services numérique et consulting	1.25	0.04	11
Aéronautique	1.40	0.11	18
Construction	1.65	0.04	6
Transport national et international & transit	2.24	0.57	90
Industrie de luxe	2.52	0.36	21
Automobile	2.71	0.38	58
Industrie agroalimentaire	3.29	0.41	53
Télécommunication	3.15	0.00	6
Gestion de la relation client	3.41	0.19	34
Textile	3.38	0.00	6
Produit Pharmaceutique	3.64	0.27	21
Industrie de la pêche	3.73	0.10	19

A ’-’ indicates the sample size was too small for the statistic to be calculated.

The means of Technology Acceptance (TA) vary significantly across different sectors. For example, the IT sector has an average of 1.15 (SD = 0.08), while the fishing sector has an average of 3.73 (SD = 0.10). Other sectors also show significant variations, with means ranging from 1.25 (Digital Services and Consulting) to 3.64 (Pharmaceutical Products).

The standard deviations associated with the means also indicate differences in the variability of scores within each sector. For instance, the telecommunications sector has a zero variance (SD = 0.00), suggesting high consistency of scores in this sector, while sectors like National and International Transport & Transit show greater variability (SD = 0.57).

These results suggest that significant differences in TA scores may be attributed to the specific char- acteristics of each industrial sector. For instance, sectors such as pharmaceuticals and the food industry, which have high means, may reflect particular characteristics influencing TA scores, such as more complex industrial processes or specific requirements. In contrast, sectors with lower means, such as IT and digital services, might show different trends due to the different nature of their activities or business models.

The ANOVA confirms that the industrial sector plays a crucial role in the observed variations in TA scores. The substantial differences between sectors highlight the importance of considering the industrial sector when analyzing this variable. The results also emphasize the need to account for sample size and variance within each sector to accurately interpret the observed differences.

C. Post-hoc Analysis

1) Technology acceptance: The analysis of Technology Acceptance scores reveals marked differences across industries, high- lighting significant variations in how different sectors adopt and use technological tools. The results, based on a t-test and adjusted using the Tukey HSD method to correct for multiple comparisons, show that the IT sector has a notably lower average TA score (M = 1.15, SD = 0.08) compared to all other industries, indicating a lower level of acceptance in this field.

TA scores for IT are significantly lower than those for all other sectors. For example, the average score for the luxury industry (M = 2.52, SD = 0.36) is substantially higher than that for IT, with a statistically signif- icant difference (p ¡ 0.001). Similarly, the score for the food industry (M = 3.29, SD = 0.41) is significantly higher than that for IT (p ¡ 0.001). Scores for the telecommunications sector (M = 3.15, SD = 0.00), customer relationship management (M = 3.41, SD = 0.19), and textiles (M = 3.38, SD = 0.00) are also significantly higher than those for IT, with p-values all less than 0.001.

When comparing other non-IT industries, significant differences are also observed. For instance, the average score For the automotive sector (M = 2.71, SD = 0.38), the average score is significantly higher than that for national and international transport & transit (M = 2.24, SD = 0.57) (p ¡ 0.001). The score for the food industry is also significantly higher than that for national and international transport & transit (p ¡ 0.001). Additionally, the score for the luxury industry is significantly lower than for the food industry (p ¡ 0.001) and the fishing industry (p ¡ 0.001).

The results reveal notable differences between specific industries. The average score for the aerospace sector (M = 1.40, SD = 0.11) is significantly lower than those for the luxury industry (M = 2.52, SD = 0.36) and the fishing industry (M = 3.73, SD = 0.10), with p-values all less than 0.001. Similarly, the score for the construction sector (M = 1.65, SD = 0.04) is significantly lower than those for the luxury, automotive, food, telecommunications, customer relationship management, textiles, pharmaceutical, and fishing industries, with p-values ranging from 0.025 to ¡ 0.001.

These results highlight significant variations in technology acceptance across different sectors, with the IT industry showing the lowest scores and sectors like fishing and pharmaceuticals displaying the highest scores. The observed differences underscore the importance of considering the specific context of each sector when evaluating and improving technology adoption.

2) Needs identification: In Section III on Needs Identification, issues related to real-time monitoring are addressed. Statistical data shows that the Information Technology industry has a significantly lower average for real-time monitoring needs compared to several other sectors. For instance, the average for IT (M = 1.15, SD = 0.08) is significantly lower than that for national and international transport & transit (M = 2.24, SD = 0.57), with a p-value ¡ .001. This trend is also observed in other sectors such as the luxury industry (M = 2.52, SD = 0.36), automotive (M = 2.71, SD = 0.38), and food industry (M = 3.29, SD = 0.41), all showing p-values ¡ 0.001 compared to IT.

For the digital services and consulting sector, the average (M = 1.25, SD = 0.04) is also significantly lower compared to these sectors, with p-values ¡ 0.001. Similar results are found for aerospace, construction, and other industries, with averages consistently lower than those for sectors like pharmaceuticals (M = 3.64, SD = 0.27) and fishing (M = 3.73, SD = 0.10), all with p-values ¡ 0.001.

These significant differences suggest that the IT industry and digital services encounter less pro- nounced real-time monitoring issues compared to other sectors, potentially indicating different needs or varying levels of technological maturity in real-time monitoring.

3) AI Solution acceptance: In Section IV of the study, concerning AI Solution Acceptance (SAAI), a t-test was conducted for each question to examine differences between industry groups, with corrections for multiple comparisons using Tukey HSD adjustment. The results reveal significant differences for each question asked.

For SAAI Question 1, which deals with real-time visibility into vehicle fuel consumption, the IT industry (M = 1.15, SD = 0.08) shows a significantly lower average compared to sectors such as National and International Transport & Transit (M = 2.24, SD = 0.57), Luxury Industry (M = 2.52, SD = 0.36), and Automotive (M = 2.71, SD = 0.38), with p-values ¡ .001 for all these comparisons. Similarly, for SAAI Question 2 on CO2 emissions visibility, the averages in the IT industry are also lower compared to other sectors, with significant differences (p ¡ .001). The same trend is observed for Vehicle Localization (SAAI 3), Driver Status (SAAI 4), Detailed Delivery Times (SAAI 5), and Driver Statistics (SAAI 6), all showing lower averages in the IT sector compared to other industries, with p-values less than .001. These results indicate that responses from companies in the IT sector show a significantly lower acceptance of AI solutions compared to other industrial sectors.

D. Verification of Hypotheses

1) Hypothesis 1: Only companies with large logistics systems are interested in integrating AI into their systems: To test this hypothesis, we analyzed the correlation between the size of the logistics system and interest in AI. The size of the logistics system was categorized into three groups: "small," "medium," and "large." Interest in AI was measured by a dichotomous variable (yes/no). A Chi-square test was conducted to assess the relationship between these two variables. The results showed a Chi^2 of 15.75 with a p ¡ .001, indicating a significant relationship. This suggests that companies with larger logistics systems are more likely to be interested in AI.

2) Hypothesis 2: The perceived complexity of AI tools slows down their adoption in logistics: To evaluate this hypothesis, we used linear regression analysis to study the impact of perceived com- plexity on AI adoption. Perceived complexity was measured on a scale from 1 to 5, while AI adoption was measured by an adoption rate. The regression results showed a coefficient of -0.46 with a p ¡ .001. This indicates that perceived complexity has a significant negative effect on AI adoption, confirming that as AI tools are perceived as more complex, adoption rates are lower.

3) Hypothesis 3: Companies show a high need for AI solutions: To test this hypothesis, we performed an analysis of variance (ANOVA) to compare the levels of need for AI across different industry sectors. The need for AI solutions was measured by an assessment score across various sectors. The ANOVA produced a result with F(12, 338) = 95.87 and p ¡ .001, showing significant differences in the need for AI solutions between sectors. This suggests a strong demand for AI solutions in certain sectors, particularly those with higher scores such as the food industry and pharmaceuticals.

E. Limitations and Future Research

The limitations of this study on the integration of AI in road logistics in Morocco are evident on several levels. First, the survey sample is predominantly composed of practitioners and decision-makers within European SMEs, which may introduce cultural and contextual bias when applying the findings to Morocco. Additionally, although the study focuses on key variables such as satisfaction with internal information (SII), level of innovation (LI), adoption rate (AR) of AI technologies, and availability of qualified human resources (QHR), other contextual factors specific to the Moroccan market, such as local regulations, infrastructure, and technological maturity of companies, have not been sufficiently addressed.

Furthermore, the methodology relies primarily on self-reported data collected through online question- naires, which may lead to response or social desirability biases, affecting the reliability of the results. Finally, while the quantitative approach provides valuable insights, it limits the depth of analysis of organizational and cultural dynamics that may influence AI adoption in logistics in Morocco. These factors should be considered when interpreting the results, and further research, including qualitative studies, would be necessary for a more comprehensive understanding of the topic.

In my future research, I plan to develop an innovative application specifically designed to address the key challenges of road logistics. This application will aim to improve the safety, efficiency, and sustainability of transport operations by tackling the critical issues identified in the current study.

1) Reducing road fatalities: The application will incorporate advanced driver behavior monitoring fea- tures. For instance, it could provide real-time alerts for dangerous driving behaviors, such as speeding or abrupt lane changes, while also offering reminders to encourage regular breaks and prevent driver fatigue. Additionally, detailed reports on driver behavior will be generated, allowing managers to take proactive measures to enhance safety.

2) Reducing CO_2 emissions: Another central focus of this application will be to reduce CO2 emissions. By optimizing delivery routes, the application will decrease the distances traveled and shorten travel times, leading to a significant reduction in greenhouse gas emissions. Moreover, it will encourage the adoption of more environmentally friendly vehicles by providing comparative analyses of the environ- mental performance of different vehicles in the fleet.

3) Real-time package tracking: The application will offer a real-time package tracking solution, en- hancing transparency and customer trust. With an integrated GPS tracking system, both customers and businesses will be able to monitor the exact location of their shipments at every stage of the delivery process, minimizing the risk of loss or delay.

4) Driver attendance tracking: The application will facilitate driver attendance tracking, enabling more rigorous management of working hours, breaks, and routes taken. This detailed tracking will contribute not only to better human resource management but also to preventing fatigue-related accidents and en- suring compliance with labor standards.

This application will provide a comprehensive response to the current challenges in road logistics by combining safety, efficiency, and sustainability. It represents a significant advancement in how transport operations can be managed and optimized while addressing the environmental and safety issues that are more critical today than ever.

V. Conclusion

The integration of AI into the logistics sector represents a major advancement towards optimizing processes and solving critical issues such as road mortality, CO2 emissions, and package tracking. The study revealed that AI offers promising solutions to enhance road safety through autonomous driving systems and driver assistance devices, despite challenges such as high costs and regulatory concerns. Companies that successfully adopt these technologies experience a notable reduction in road incidents, contributing both to safety and efficiency in logistics operations. Regarding CO2 emissions, AI systems enable more efficient management of routes and loads, leading to a significant decrease in carbon footprint. Supply chain optimization algorithms and fleet management have shown positive results, although implementation requires substantial investments and adaptation of existing infrastructure. As for package tracking, AI-based technologies, such as real-time traceability systems and data analytics, have significantly improved transparency and reduced delivery errors, despite challenges related to integration with existing systems and managing vast amounts of data. The study also highlighted several obstacles to AI adoption in logistics. Technological complexity, high initial costs, and regulatory and ethical issues are major challenges for companies. Particularly, Moroccan companies show growing interest in AI, with more marked adoption in specific sectors such as agri-food and pharmaceuticals, while other sectors, like IT, face slower adoption rates. To fully capitalize on the benefits of AI, it is recom- mended that companies invest in training their human resources, modernize their infrastructure, and develop strategies tailored to the specific needs of each sector. Future research should explore the specific applications of AI in different sectors and evaluate the long-term impacts on logistics performance. By examining inter- national best practices, it will be possible to provide more precise recommendations to Moroccan companies. In summary, although significant challenges remain, AI holds considerable potential to transform the logistics sector. The success of this transformation will depend on companies' ability to overcome these obstacles and invest in the necessary technologies to optimize their operations.

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