

Review

How Can Autonomous Truck Systems Transform North Dakota's Agricultural Supply Chain Industry?

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Abstract

The swift advancements in autonomous vehicle systems have facilitated their implementation across various industries, including agriculture. However, studies primarily focus on passenger vehicles, with fewer examining autonomous trucks. Therefore, this study reviews autonomous truck systems implementation in North Dakota's agricultural industry to develop comprehensive technology readiness frameworks and strategic deployment approaches. The review integrates systematic literature review and event history analysis of 52 studies, categorized using Social–Ecological–Technological Systems framework across six dimensions: technological, economic, social change, legal, environmental, and implementation challenges. The Technology Readiness Level (TRL) analysis reveals 39.5% of technologies achieving commercial readiness (TRL 8–9), including GPS/RTK positioning and V2V communication demonstrated through Minn-Dak Farmers Cooperative deployments, while gaps exist in TRL 4–6 technologies, particularly cold-weather operations. Nonetheless, challenges remain, including legislative fragmentation, inadequate rural infrastructure, and barriers to public acceptance. The study provides evidence-based recommendations that support a strategic three-phase deployment approach for the adoption of autonomous trucks in agriculture.

Keywords: agricultural logistics; autonomous trucks; supply chain optimization; North Dakota



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1. Introduction

The convergence of artificial intelligence, sensor technologies, and autonomous systems is fundamentally reshaping transportation paradigms across multiple sectors, with agricultural supply chains emerging as a critical frontier for technological transformation. These technologies enable vehicle navigation and task execution without human intervention [1]. Although much attention has been paid to their applications in passenger transportation and urban mobility, autonomous trucks are a watershed moment, with enormous promise for industries that rely on logistics and heavy-duty transport [2]. Therefore, the integration of Autonomous Truck Systems (ATS) into agricultural supply chains represents a paradigm shift from traditional logistics models toward precision-driven, technology-enabled operations that can address persistent challenges of labor shortages, operational inefficiencies, and supply chain vulnerabilities [3].

North Dakota's agricultural landscape exemplifies the transformative potential of autonomous trucking technologies, particularly given the state's position as a leading producer of wheat, soybeans, and sugar beets, coupled with its vast geographical expanses and seasonal operational demands [4,5]. The state's agricultural supply chain spans approximately 39 million acres of farmland, generating over \$7 billion in annual agricultural output, yet faces critical challenges, including an aging workforce, limited transportation infrastructure, and extreme weather conditions that significantly impact logistics efficiency [3]. These regional characteristics position North Dakota as an ideal testbed for examining how autonomous truck systems can address sector-specific challenges while advancing broader agricultural innovation objectives.

Thus, recent technological demonstrations, including the Minn-Dak Farmers Cooperative's leader-follower platooning system for sugar beet transportation, provide empirical evidence of ATS viability in agricultural contexts [6]. However, existing studies exhibit significant gaps in comprehensive analysis of technology readiness levels, systematic assessment of implementation challenges across multiple agricultural supply chain segments, and region-specific evaluation frameworks that account for climatic, regulatory, and infrastructure constraints unique to agricultural environments [7,8]. Additionally, research on the deployment of autonomous vehicles in cities and highways often overlooks their use in rural and agricultural areas [9]. Moreover, most studies concentrate on technological progress or economic viability while neglecting the examination of legal, social, and environmental aspects [10]. Thus, the literature lacks integrated methodological approaches that combine systematic literature analysis with real-world deployment evidence to inform strategic implementation pathways.

Accordingly, this study addresses these critical knowledge gaps by providing a comprehensive review of autonomous truck systems and their implementation in North Dakota's (ND) agricultural sector. Specifically, we develop a comprehensive Technology Readiness Level (TRL) assessment framework, calibrated explicitly for agricultural autonomous truck systems, systematically evaluating relevant studies to determine technology maturity across different domains. This framework enables evidence-based prioritization of technology development investments and deployment strategies. Second, we establish a novel multidimensional categorization system that systematically analyzes autonomous truck implementation across challenge dimensions, providing stakeholders with structured insights for addressing adoption barriers. Third, we introduce a strategic three-phase deployment methodology that aligns technology readiness levels with implementation timelines, risk mitigation strategies, and regional infrastructure requirements specific to North Dakota's agricultural supply chain context.

The study employs an innovative dual-methodology approach that combines Systematic Literature Review (SLR) with Event History Analysis (EHA), integrating peer-reviewed academic research with industry reports, conference proceedings, and real-world deployment data. This methodological innovation enables comprehensive capture of both theoretical frameworks and practical implementation insights, addressing the traditional disconnect between academic research and industry practice in autonomous vehicle deployment studies [10]. The study systematically analyzes studies from journal databases, complemented by stakeholder perspectives from the Upper Great Plains Transportation Institute's 2024 Autonomous Trucking Conference, ensuring contemporary relevance and practical applicability.

Significantly, this study extends beyond regional agricultural contexts to inform broader autonomous truck deployment strategies in rural and agricultural environments globally. As agricultural sectors worldwide confront similar challenges, this study's findings provide transferable insights for policy development, infrastructure planning, and

technology adoption strategies. The research contributes to emerging discussions on precision agriculture, sustainable supply chain transformation, and adoption of rural technology, while establishing methodological foundations for future autonomous truck research in agricultural contexts. The study's implications are particularly relevant for policymakers addressing rural infrastructure development, technology companies developing agricultural automation solutions, and agricultural cooperatives evaluating investments in autonomous systems. By providing evidence-based technology readiness assessments, systematic challenge identification, and strategic implementation frameworks, this study enables informed decision-making for stakeholders navigating the complex intersection of agricultural innovation, autonomous truck systems, and regional economic development priorities.

The remainder of the study is organized as follows: Section 2 reviews existing studies on the development of autonomous truck systems, with a particular emphasis on the state of North Dakota. Section 3 presents the methodology used to ascertain this study's objective. Section 4 addresses the research questions mentioned in Section 3, while Section 5 concludes this study.

2. Status of Autonomous Trucks Development

The rapid advancements in autonomous vehicle technology have sparked a growing interest in developing autonomous trucks, which have immense potential to revolutionize the logistics and transportation industry [11,12]. Autonomous vehicles, including passenger cars and commercial trucks, have been a primary focus of research and development in recent decades, with significant progress made in object detection, navigation, and decision-making algorithms [13]. While much of the attention has been focused on autonomous cars, there is a consensus among industry experts that autonomous trucks are likely to become commercially available sooner than their passenger vehicle counterparts [12]. This is due to the potential benefits of autonomous trucks, such as improved safety, efficiency, and cost-effectiveness, which make them particularly appealing for long-haul freight transportation. Although scientific studies on autonomous trucks have been relatively limited compared to the extensive work performed on autonomous cars, a rapidly growing body of literature and industry focus is emerging in this field [14,15].

Existing studies reveal a global interest in developing autonomous trucks [16]. Researchers and industry experts worldwide have explored various aspects of autonomous truck technology, including control systems, navigation algorithms, maintenance planning, and economic considerations. Interestingly, the literature on autonomous vehicles extends beyond the land-based transportation industry, with studies examining the potential opportunities for using autonomous vessels in logistics. This suggests that the broader concept of autonomous transportation is not limited to road-based vehicles but is being explored across different modes of transportation, highlighting the far-reaching significance of this technological revolution [17]. In a global context, the United States has emerged as a key player in the development of autonomous trucks [18]. Thus, researchers and industry stakeholders in this geographical area are particularly focused on addressing the unique challenges and opportunities presented by the introduction of autonomous trucks, including the potential impact on the truck-driving workforce, the integration of these vehicles into existing transportation infrastructure, and the public perception of autonomous freight transportation [16,19].

North Dakota is emerging as a pivotal testing ground for autonomous trucking technology in the United States, with its unique geographical and economic conditions driving adoption [20]. The state's vast agricultural landscape, coupled with long transport distances and labor shortages, presents an ideal use case for Avs [21]. Autonomous trucking

has already seen implementation through projects such as the Minn-Dak Farmers Cooperative's leader-follower platooning system, where sugar beets are transported between piling locations and processing facilities using a human-driven lead vehicle followed by an autonomous truck (see Figure 1). This system, operational during the 2023–2024 harvest season, leverages advanced technologies such as real-time kinematic GPS and encrypted vehicle-to-vehicle (V2V) communication to ensure seamless operations in rural areas. The program demonstrated significant resilience under harsh winter conditions, showcasing the technology's ability to consistently navigate snow, ice, and extreme cold. Such advancements highlight North Dakota's commitment to pioneering AV integration in the agricultural sector. Therefore, it is necessary to note that the goal of developing the Minn-Dak Farmers' Cooperative is not to eliminate the driver but rather to offer an alternative when qualified drivers are unavailable.



Figure 1. Pilot deployment Route 1 of autonomous trucks by Minn-Dak [6].

Similarly to the Brønnøy Kalk project with Volvo Autonomous Solutions [22], which focuses on deploying a commercial autonomous transport solution for transporting limestone from a mine to a crusher, Figure 2 shows technology deployment across sequential supply chain stages. This indicates process flow and technological interdependencies between production, processing, and distribution operations. At the Production level, ATS relies on LiDAR for precision navigation in unstructured farm environments, enabling 3D mapping and real-time obstacle detection. AI-powered navigation systems dynamically adjust routes based on soil conditions, crop placement, and environmental factors, ensuring smooth movement across fields [23]. Additionally, autonomous harvesting integration allows seamless coordination between harvesters and autonomous trucks, reducing downtime and labor dependency [24,25]. Vehicle-to-Everything (V2X) communication enhances connectivity, enabling real-time data exchange between trucks, farm machinery, and storage units for synchronized workflow. At the Processing and Storage stage, GPS and Real-Time Kinematic (RTK) positioning provide high-precision route tracking, ensuring efficient transport of crops from fields to silos, cold storage, or processing facilities [26]. Fleet telematics and IoT sensors enable real-time monitoring of perishable goods, ensuring quality control while optimizing fuel efficiency [27]. Moreover, autonomous docking and loading systems streamline truck alignments for automated grain loading and unloading, thereby reducing human intervention and minimizing waste [28]. Conversely, cloud-based analytics enhance predictive maintenance, fuel efficiency, and route optimization, ultimately minimizing supply chain disruptions [29].

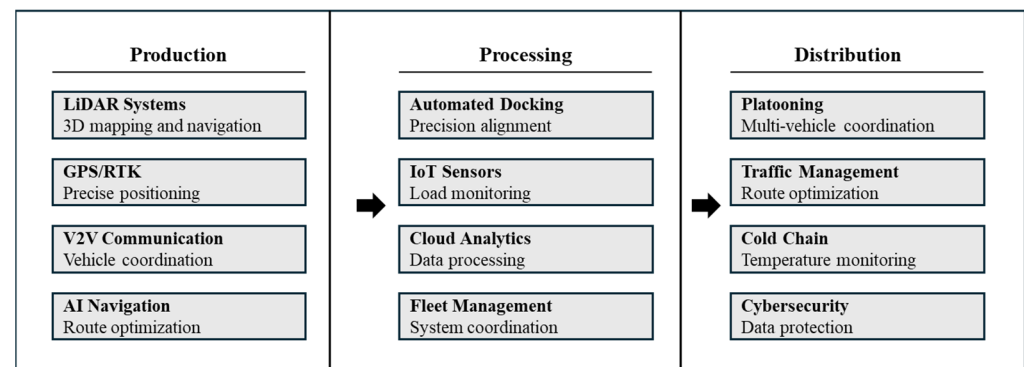


Figure 2. Key enabling technologies of ATS in agricultural supply chains.

In the distribution and logistics phase, platooning technology enables the coordinated movement of multiple autonomous trucks, reducing fuel consumption through aerodynamic efficiency and synchronized acceleration [30]. Smart traffic management systems optimize delivery routes by leveraging real-time traffic data, AI-driven congestion analysis, and infrastructure integration. Additionally, cold chain monitoring sensors ensure precise temperature and humidity control for perishable goods, securing food quality during transit to markets or export hubs [31]. Cybersecurity frameworks and blockchain integration safeguard supply chain transparency, securing transaction data and preventing fraud [32]. By integrating these technologies across all three supply chain dimensions, ATS significantly enhances operational efficiency, reduces costs, minimizes environmental impact, and modernizes North Dakota's agricultural logistics infrastructure.

However, the state faces challenges in fully leveraging autonomous trucking [20]. Infrastructure is a critical concern, as many rural highways lack the necessary features, such as clear lane markings, robust connectivity, and smooth road surfaces, to support AV deployment. According to Brian Routhier [33], most autonomous trucks operate in a mixed environment alongside traditional vehicles, which raises concerns regarding safety and traffic management. To address this, North Dakota has taken steps to align legislation with AV requirements, allowing limited platooning operations since 2019 [34]. However, updates are needed to enable fully driverless truck dependency and expand deployment to non-trunk highways. Thus, autonomous trucks should be able to operate independently on the road, without accompanying vehicles. Beyond legislation, public and industry trust in AV technology is vital. State initiatives, such as engaging tribal and rural communities to build awareness and technical capacity, emphasize collaborative approaches to overcome skepticism [35]. Hence, as a major exporter in the Northern Great Plains [36], these efforts, combined with technological advancements, may position North Dakota as a leader in autonomous trucking innovation in the region, with significant implications for the agricultural sector and beyond.

3. Research Methodology

Comprehensive literature studies were conducted to provide an overview of the status of autonomous trucks in North Dakota's agriculture industry, their impact on the supply chain, and the challenges they encounter. The integration of a Systematic Literature Review (SLR) by Mengist et al. [37] and Event History Analysis (EHA) employed by Van de Ven [38] are utilized to address the following research questions.

- What is the status of autonomous trucks in ND's agricultural industry?
- How does AT impact ND's agricultural supply chain?
- What are the pressing challenges of AT implementation in ND?

The SLR collects studies from reputable academic databases and systematically analyzes them to select the most relevant studies. However, the EHA approach focuses on collecting archival data from events within the innovation system; data is primarily derived from reports, periodicals, newspapers, and press releases. Figure 3 stipulates the framework of the methodology.

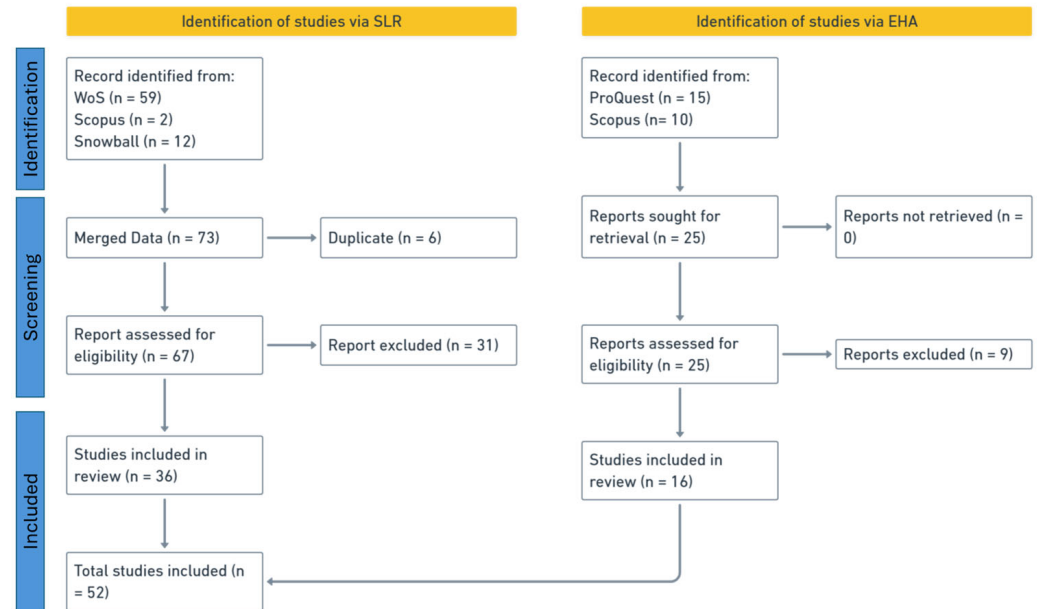


Figure 3. Methodological framework.

The study is partitioned into two sections. Initially, the SLR approach is implemented by employing two research databases: Scopus and Web of Science. These databases are used because they have the most influential papers [39,40]. The primary search terms were Autonomous Trucks or Autonomous Vehicles and Agriculture. This topic is not unfamiliar to scholars in this discipline, as evidenced by the extensive collection of peer-reviewed articles. To ensure that the search results were relevant to the study’s interests, the search was restricted to “Autonomous Truck*” OR “autonomous vehicle*” AND “agric*” AND “United State*”, excluding non-English papers, ultimately yielding 61 research publications. A snowball technique is also employed to obtain more papers, resulting in an additional 12 papers. Thus, the references of three studies, such as Jones et al. [41], Bridgelall et al. [42], and Kim et al. [15], are used to identify the 12 additional studies. After scanning the titles and abstracts, nine duplicate studies were found.

Secondly, considering the technical nature of this topic, data were gathered from other academic and non-academic literature using the EHA approach. The search was conducted in the ProQuest database, yielding 15 academic reports and theses. Additionally, 10 presentation reports from the Autonomous Trucking Conference, organized by the Upper Great Plains Transportation Institute (UGPTI) on 16–17 October 2024, in Bismarck, ND, were included, bringing the total to 25. Stakeholders from the transportation and autonomous vehicle industries, technical experts, highway safety specialists, enforcement personnel, regulatory agency staff, local and tribal government staff, and researchers comprised more than 120 attendees at the conference. The participants exchanged ideas and collaborated to identify shared interests and concerns regarding autonomous trucks in North Dakota.

After reviewing the full texts of the 89 studies, using the eligibility criteria outlined in Table 1, 52 essential studies were selected. The information gathered using the methodology, as mentioned earlier, is highlighted as innovative approaches to enhance the localization, control, and trajectory monitoring of autonomous machinery in agricultural environments.

Some publications examine the use of deep learning and low-cost positioning systems to improve the accuracy and efficiency of these vehicles, representing an increasing trend toward accessible precision agriculture. Furthermore, they explore the challenges and opportunities of deploying autonomous mobile robots in dynamic agricultural contexts. This includes the possibility for applications in regions such as the broad agricultural expanses of North Dakota. This research collectively emphasizes the transformative potential of autonomous systems to enhance agricultural productivity and sustainability.

Table 1. Eligibility criteria for relevant studies.

Eligibility	Exclusion Criteria	Inclusion Criteria
1	The study is unrelated to agriculture or farming.	The study focuses on autonomous trucks or vehicle systems.
2	It lacks relevance to North Dakota or similar regions.	It relates to the agricultural or farming sector.
3		It mentions explicitly or applies to North Dakota.

Moreover, the selected studies are categorized based on the Social–Ecological–Technological Systems (SETS) framework. The SETS framework recognizes that complex systems emerge from the dynamic interactions between social, ecological, and technological dimensions, with each dimension containing multiple interconnected components that collectively determine system outcomes [43,44]. Hence, the classifications of the studies are presented in Tables 2 and 3. It serves as a basis to address the research questions.

3.1. Categorization of Relevant Papers

As presented in Table 2, organizing and contextualizing the selected papers within the domain of autonomous trucks and vehicle systems in agriculture is crucial through systematic categorization of research articles. The analysis of the categorized papers revealed several significant trends and gaps. The Technological and Economic dimensions represent the technological system encompassing innovation capabilities and resource mobilization; Social Change and Legal dimensions constitute the social system including institutional frameworks, governance structures, and community acceptance; Environmental and Challenges dimensions reflect the ecological system and cross-system barriers that emerge from misalignments between social, ecological, and technological components. This framework emphasizes that successful technology adoption requires coordination across all three systems, where technological readiness should align with social acceptance and institutional support while addressing ecological sustainability constraints and systemic implementation challenges [45].

Considering the EHA approach, further reports and theses were systematically classified into the exact six predetermined dimensions. Compared to the previously examined corpus of peer-reviewed papers through SLR, the EHA data also emphasizes the dominance of the Technological and economic categories. These papers strongly emphasize developments in automation systems and economic feasibility, aligning with the trends in academic literature. However, unlike the SLR categorization, the EHA categorization has a slightly higher representation in the Social Change category, particularly when investigating community-level implications and acceptance of autonomous agricultural technologies. As presented in Table 3, the Legality and Environment categories are underexplored in both datasets, indicating a persistent lack of attention to regulatory frameworks and environmental consequences. Furthermore, the Challenges category in the EHA data highlights operational and infrastructure obstacles similar to those identified in academic studies,

but with greater emphasis on the practical challenges stakeholders encounter during real-world implementations.

Table 2. Category of selected papers from the SLR approach.

Author	Technological	Economic	Social Change	Legality	Environment	Challenges
Bayar et al. [46]	✓	✓				
C. Badgujar et al. [47]	✓	✓			✓	
Guo & Zhang [48]	✓	✓				
Liu et al. [49]	✓				✓	✓
Zha et al. [50]	✓				✓	
Kassai et al. [19]	✓				✓	✓
Durand-Petiteville et al. [51]	✓	✓			✓	
C. Badgujar et al. [52]		✓			✓	✓
Hunter et al. [53]	✓				✓	
C. M. Badgujar et al. [54]	✓	✓				
Mack et al. [55]			✓	✓		✓
Faryadi & Mohammadpour Velni [56]	✓				✓	✓
Bell et al. [57]	✓	✓				
Neupane et al. [58]	✓	✓	✓		✓	✓
Alves Nogueira et al. [59]	✓		✓			✓
Joseph D. Rounsaville et al. [60]						✓
Badgujar et al. [61]	✓		✓			✓
Li et al. [62]	✓					✓
Deka et al. [63]	✓			✓		
Carrière & Hermand [64]	✓					
Chi et al. [65]		✓		✓		
Kim et al. [15]		✓			✓	
Bridgelall [66]		✓	✓			
Bridgelall et al. [42]	✓	✓	✓	✓	✓	✓
Joshua Krank [67]	✓			✓		
Etezadi & Eshkabilov [68]	✓					✓
Talebian & Mishra [69]		✓	✓			✓
Uddin [70]		✓	✓		✓	✓
Du et al. [71]	✓	✓				
Fagnant & Kockelman [72]		✓	✓	✓	✓	✓
Pedersen et al. [73]	✓	✓				
Sara et al. [74]		✓	✓	✓		✓
Jones et al. [41]	✓					
Stock & Gardezi [75]		✓		✓		✓
Guangnan Chen [76]	✓				✓	
Mirzazadeh et al. [77]		✓	✓	✓		✓

Table 3. Category of selected papers from the EHA approach.

Author	Technological	Economic	Social Change	Legality	Environment	Challenges
Pederson [78]	✓					
Christopher Joseph Duchsherer [79]	✓		✓			
Niederluecke et al. [80]					✓	✓
Delavarpour et al. [81]	✓					
Dooley [82]				✓		
Mirzazadeh [83]			✓		✓	✓
Richard Bishop [84]	✓	✓	✓			
Greg Lardy [21]		✓				✓
Maynard Factor [34]	✓			✓		✓
Mike Metzger [6]	✓	✓				✓
John Sova [85]				✓		
Brian Routhier [33]			✓	✓		✓
Russ Buchhiz [86]	✓	✓		✓		
Raj Bridgelall [87]	✓				✓	✓
Heidi Corcoran [35]	✓	✓	✓	✓		
Ron Hall [88]		✓	✓	✓		✓

This integrated analysis demonstrates complementary insights from academic and event history data. While peer-reviewed research provides theoretical and methodological rigor, EHA reports offer practical and contextual insights, enhancing our understanding of the factors influencing the adoption and integration of self-driving vehicles in agriculture. Together, these analyses provide a comprehensive platform for addressing technological, economic, and societal needs in advancing autonomous systems in North Dakota and elsewhere.

3.2. Technology Readiness Level Assessment

To systematically evaluate technology maturity, each technological component identified in the literature was assessed using the nine-level Technology Readiness Level (TRL) framework developed by NASA. As illustrated in Figure 4, the TRL assessment process involved four stages.

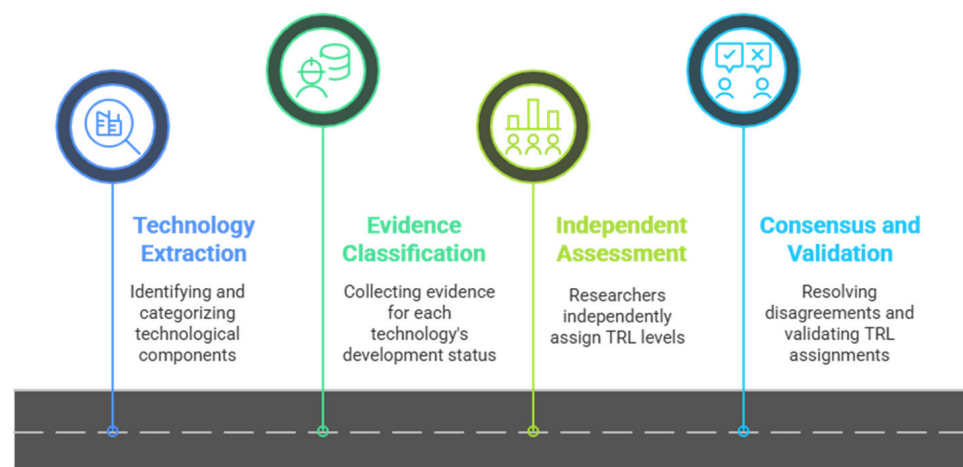


Figure 4. Technology readiness level assessment process.

Stage 1: Technology Extraction—All technological components mentioned across the 52 selected studies were systematically identified and categorized into six primary domains: navigation systems, communication systems, control algorithms, sensor technologies, integration platforms, and operational support systems.

Stage 2: Evidence Classification—For each technology, evidence was collected regarding development status, testing environment, performance validation, and commercial deployment. Evidence types included laboratory studies (TRL 1–4), field testing programs (TRL 5–6), pilot deployments (TRL 7–8), and operational implementations (TRL 9). Assessment criteria specifically considered North Dakota’s agricultural environment, including harsh weather conditions, limited rural infrastructure, and economic constraints as described in the literature

Stage 3: Independent Assessment with Inter-Rater Reliability Measures—Four researchers independently assigned TRLs to each technology based on the highest level of maturity evidence found in the literature. Each assessor evaluated all 43 technologies using standardized TRL criteria adapted for agricultural applications. Inter-rater reliability was quantified using Fleiss’s kappa (k) for categorical agreement among multiple raters and the Intraclass Correlation Coefficient (ICC) for consistency assessment. The multiple reliability measures are calculated using the following equations:

$$k = \left(\frac{P_0 - P_e}{1 - P_e} \right) \quad (1)$$

$$ICC = \frac{(MSR - MSE)}{\left(MSR + (k - 1)MSE + k \left(\frac{MSC - MSE}{n} \right) \right)} \quad (2)$$

Stage 4: Consensus and Validation—Technologies with initial disagreements underwent structured consensus resolution where disagreeing assessors presented supporting evidence for their ratings, specific agricultural application criteria were refined, and independent reassessment was conducted using clarified criteria. Final TRL assignments were validated against current commercial availability and deployment status in agricultural applications. Statistical analysis was conducted using Python 3.13.3 c with bias-corrected bootstrap confidence intervals.

4. Results and Discussion

Adopting ATS in North Dakota’s agricultural supply chain marks a significant step toward improving efficiency and addressing long-standing logistical challenges. Using NVivo 14.24 to identify themes and recurring concepts, a word cloud is generated in Figure 5. The selected studies stipulate key themes, including advancements in *precision logistics*, the role of *sensors* and *monitoring technologies* in optimizing transportation operations, and the integration of *remote navigation systems* to streamline the movement of agricultural goods. Studies by Hasiri and Kermanshah [89] and Sindi and Woodman [90] indicate that autonomous trucks enhance the *harvesting-to-market process*, reducing delays, improving fuel efficiency, and mitigating labor shortages that often hinder supply chain performance. Furthermore, innovations in *control systems* and *transportation technologies* have enabled better management of large-scale farming operations across North Dakota’s vast agricultural landscapes. Although Figure 5 provides a general thematic overview, the primary analytical insights derive from the systematic six-dimensional categorization and TRL assessment frameworks presented in subsequent sections.

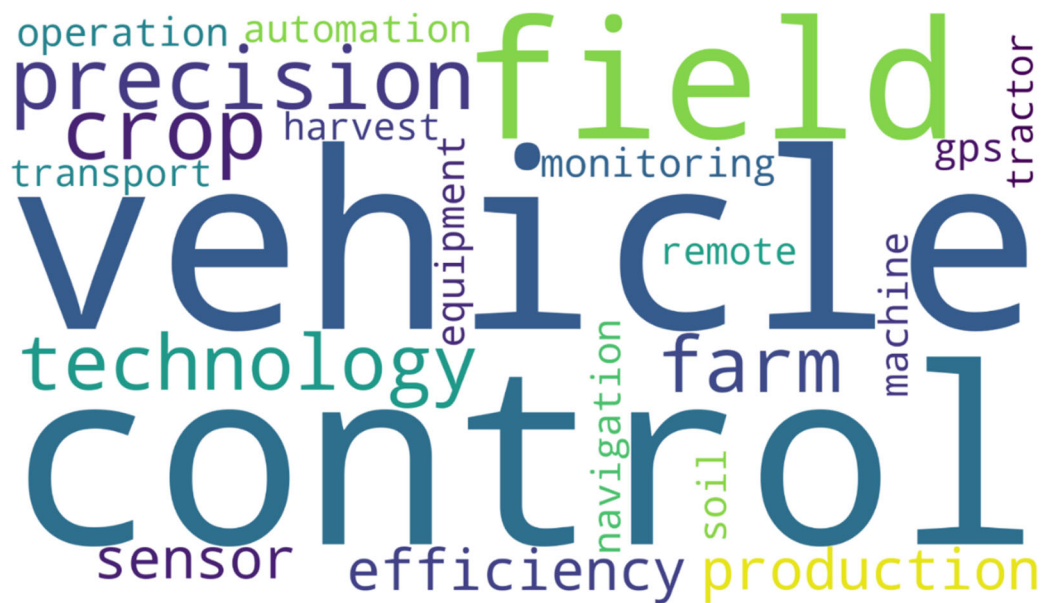


Figure 5. Word cloud of identified themes from the selected studies.

4.1. Impacts of Autonomous Trucks on the North Dakota Agricultural Supply Chain

Integrating autonomous trucks into the agricultural supply chain can transform logistics by addressing critical inefficiencies, labor shortages, and cost barriers. In North Dakota, where agriculture is a cornerstone of the economy, autonomous trucking provides a much-needed solution to challenges such as the aging trucking workforce and seasonal labor shortages. Over 60% of the state's commercial driver's license (CDL) holders are 50 or older, creating a growing gap in available drivers for long-haul and short-haul agricultural transport [86]. Autonomous trucks, such as those deployed by Minn-Dak Farmers Cooperative, mitigate these challenges by reducing dependency on human drivers while enhancing safety and hauling productivity [6].

It is essential to recognize that the feasibility of ATS varies across different segments of the ASC. For instance, transporting sugar beets from piling stations to processing plants, as seen in Figure 1, demonstrates the potential for automation on predefined, structured routes with minimal variability [6]. However, adopting autonomous trucks for field-to-piling station transport presents more significant challenges due to unstructured terrains, short travel distances, and the need for human supervision during loading and unloading. Similarly, for grain transportation, autonomous trucks could feasibly operate on routes between elevators and processing or intermodal facilities, where roads are better defined. However, the transition from fields to local grain elevators remains more complex, requiring additional technological advancements to address terrain variability and short-haul logistics. These advancements should include terrain-adaptive navigation systems such as Terrain Adaptive Navigation (TANav) and Terrain Relative Navigation (TRN) to handle uneven, unstructured farm terrain [91,92], enhanced AI-driven load handling, such as Autonomous Mobile Robots (AMRs) and Forklifts, and Predictive Analytics and Demand Forecasting, and more reliable short-haul automation, including Building management systems (BMS) to manage variable field conditions and human-assisted operations [93,94].

In addition to addressing labor shortages, autonomous trucks improve supply chain efficiency by reducing delays and optimizing transport routes [95]. Automated vehicles equipped with advanced RTK GPS systems and obstacle-detection technologies can navigate rural roads more accurately and with less downtime than traditional trucks [34]. This is particularly critical for time-sensitive agricultural products, such as sugar beets, where delays can compromise quality. The deployment of ATS also minimizes risks associated

with human error, such as overweight loads, speeding, or fatigue-related accidents [94]. For instance, automated monitoring systems ensure compliance with safety standards, reducing the likelihood of regulatory penalties and logistical disruptions.

Moreover, Figure 6 effectively illustrates the incorporation of ATS into the agricultural supply chain in North Dakota, a state renowned for its extensive production of wheat, soybeans, corn, and livestock. In North Dakota's agricultural industry, farms serve as the starting point, where crops and livestock are raised across vast rural landscapes. Once harvested, raw products are transported to processing plants, such as grain elevators and food processing facilities, where they are cleaned, milled, or packaged for distribution. Some of the processed goods are stored in facilities, including grain silos and refrigerated warehouses, which help regulate supply and manage seasonal fluctuations. Autonomous trucks are crucial in optimizing transportation across North Dakota's extensive road network, ensuring the efficient movement of goods to key locations.

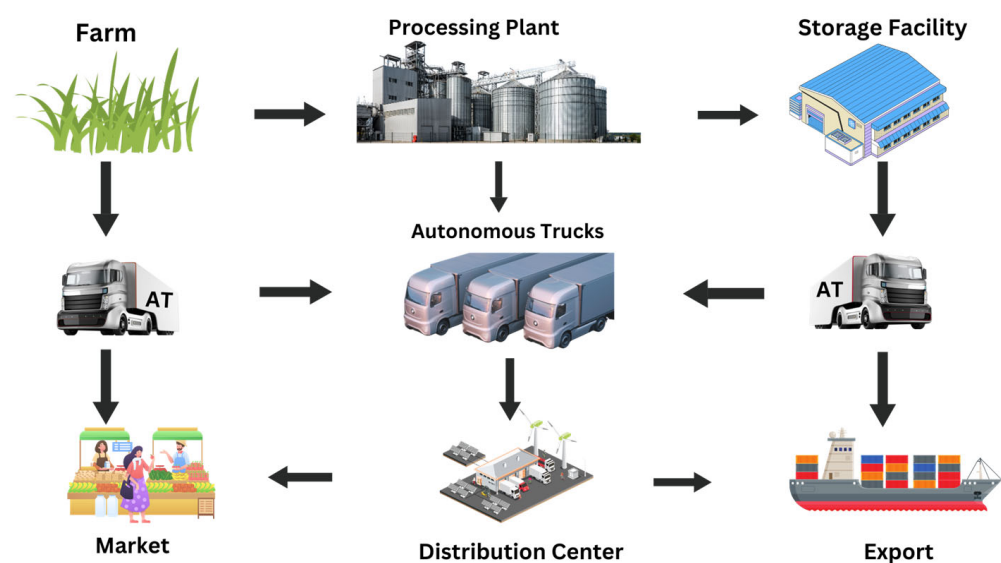


Figure 6. ATS workflow in ASC.

These trucks transport products to distribution centers and central hubs, where they are sorted and directed to various destinations. From there, agricultural products follow two main pathways: they either reach local markets, such as grocery stores, farmers' markets, and food manufacturers across North Dakota and neighboring states, or they are prepared for export, where grains, meats, and other commodities are shipped via rail or through ports like the Duluth Seaway Port on the Great Lakes. By integrating autonomous trucks, North Dakota's agricultural supply chain benefits from reduced transportation costs, optimized routing, and enhanced efficiency in delivering farm products to processing plants, storage facilities, markets, and export hubs [66]. This automation helps address labor shortages in trucking and ensures that North Dakota's agricultural output reaches both domestic and global markets more reliably and efficiently.

However, the impact of autonomous trucking extends beyond operational efficiency; it also influences the broader agricultural supply chain by enabling large-scale, centralized operations [89]. As farms consolidate and expand, the increased volume of goods to transport places a more significant strain on existing logistics networks. Autonomous trucks can alleviate these pressures by providing scalable solutions that align with the trend toward higher yields and larger production volumes. Furthermore, the ability of ATS to collect real-time data provides a competitive advantage, enabling operators to analyze

and refine their supply chain performance over time. Despite these benefits, significant challenges remain as barriers, as depicted in Tables 2 and 3.

4.2. Technology Readiness Level Analysis

The TRL assessment demonstrated methodological rigor with an ICC of 0.924, indicating very high consistency among the four independent raters. While perfect agreement was achieved for 14.0% of technologies, all assessments showed agreement within ± 1 TRLs, demonstrating practical consensus despite minor variations in ratings. The initial Fleiss's κ of 0.468 improved substantially through structured consensus resolution to $\kappa = 0.890$, achieving almost perfect agreement and validating the reliability of the TRL assessment framework for strategic technology planning in North Dakota's agricultural autonomous truck systems.

The technology maturity analysis in Table 4 revealed significant variation across autonomous truck systems, with 39.5% of technologies achieving commercial readiness (TRL 8–9) and 37.2% in demonstration or development phases (TRL 6–7). Technologies requiring further validation (TRL 4–5) comprised 18.6% of the assessment, while only 4.7% remained in early research phases (TRL 1–3), indicating substantial progress toward deployment readiness across the technology industries compared to broader automotive industry assessments, which typically show higher proportions of early-stage technologies.

Table 4. Technology readiness level distribution.

Readiness Level	TRL Category	Count	Percentage	Key Technologies
TRL 8–9	Commercial	17	39.5%	GPS/RTK, V2V Communication, Platooning
TRL 6–7	Development	16	37.2%	Computer Vision, Path Planning
TRL 4–5	Validation	8	18.6%	Cold-weather Sensors, Autonomous Docking
TRL 1–3	Research	2	4.7%	Swarm Intelligence, Blockchain

Sensor technologies demonstrated the highest commercial maturity with 62.5% of technologies at TRL 8–9, followed by navigation systems at 50% commercial readiness. This pattern reflects the essential role of sensor and navigation technologies in autonomous truck development, consistent with the European Space Agency's adoption of these technologies for space applications [96]. The communication systems demonstrated balanced growth, with 42.9% being commercial-ready, aligning with the widespread implementation of TRL frameworks across European Union research and innovation programs since the introduction of the Horizon 2020 framework [97]. Integration platforms presented the most significant development challenge, with only 16.7% achieving commercial readiness, reflecting the complex nature of system-level integration challenges documented in international TRL assessment literature [98]. Control algorithms and operational support systems both achieved 28.6% commercial readiness, indicating moderate maturity levels requiring focused development investment.

The distribution supports a strategic three-phase deployment approach, with 17 technologies ready for immediate implementation, leveraging proven capabilities demonstrated in operations such as the Minn-Dak Farmers Cooperative deployment [6]. This finding aligns with established TRL methodology principles, where the International Organization for Standardization emphasizes deployment strategies beginning with the highest-readiness technologies [99]. Therefore, the substantial proportion of technologies in advanced development phases (TRL 6–7) provides a strong pipeline for near-term commercial readiness, consistent with the systematic approach to technology assessment developed in agricultural innovation research [98]. The limited number of early-stage research tech-

nologies suggests a mature technology landscape approaching the feasibility of widespread deployment, supporting a balanced readiness assessment approach that considers multiple dimensions of technology maturity beyond technical development alone.

The TRL assessment supports a strategic three-phase implementation approach grounded in agricultural technology adoption patterns and autonomous truck development. Phase 1 (Years 1–2) focuses on deploying proven TRL 8–9 technologies on structured routes, demonstrated by operational implementations like Minn-Dak Farmers Cooperative’s leader-follower platooning system, achieving deployment within this timeframe [100]. Phase 2 (Years 3–5) prioritizes advancing TRL 4–6 technologies through strategic partnerships, with the timeline directly aligned with industry projections that autonomous trucking services will become commercially available in 2026 or later, and fully autonomous trucking expected to reach viability between 2028 and 2031 [101,102]. Phase 3 (Years 6–10) supports long-term research in TRL 1–3 technologies, reflecting the substantial investment requirements where more than \$4 billion is needed for full-journey autonomous trucks and the extended development timelines required for foundational technologies to reach commercial deployment [101]. This phased approach encompasses overlapping priority areas, allowing for flexibility to accommodate breakthrough innovations or regulatory changes that may accelerate or delay specific technology advancement trajectories.

4.3. Challenges of Autonomous Truck System Implementation

Tables 2 and 3 show that deploying ATS in agriculture encounters substantial challenges. As visualized in Figure 7, these challenges can be categorized into five criteria. Autonomous systems face technological constraints related to sensor precision, connectivity, and adaptability in unstructured agricultural settings [57,103,104]. The uneven adoption of smart farming poses operational challenges that existing sensors and navigation systems are inadequately equipped to tackle [105]. Thus, inadequate broadband systems, including unstable connectivity, limited network size, and low data transmission rates in rural regions, significantly impede real-time data transfer and remote operational capabilities, presenting a substantial obstacle to effective deployment [106]. In particular, the high capital cost of acquiring and integrating autonomous trucks is prohibitive for small and medium-sized agricultural operations from an economic perspective [21,46]. In addition to the absence of accessible financing mechanisms and uncertain return-on-investment metrics, this economic constraint exacerbates the disparity in adoption.

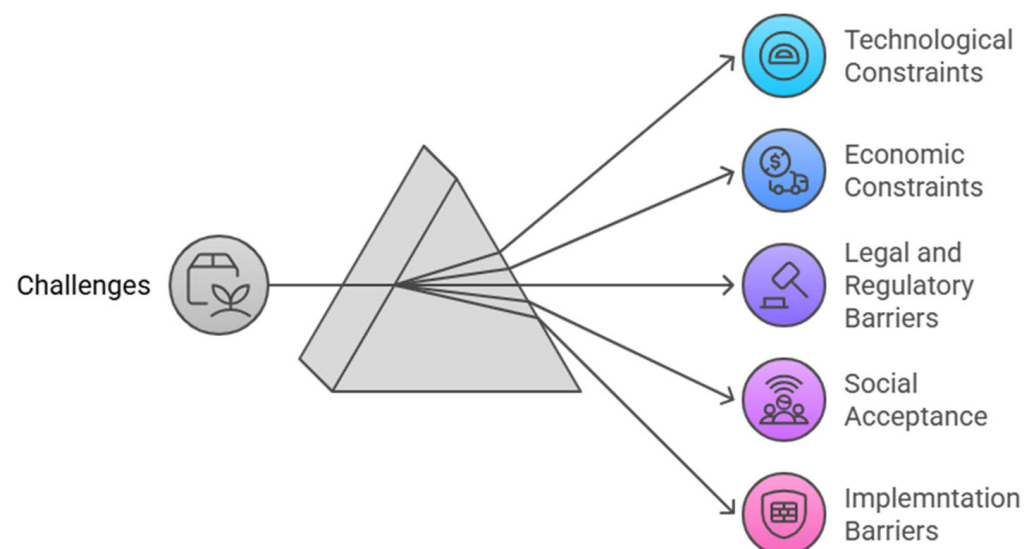


Figure 7. Challenges of AT implementation in the agricultural industry.

Legal and regulatory barriers intensify these impediments [35,82]. The fragmented regulatory framework across US states provides significant legal ambiguity, especially for agricultural supply networks that span state borders. Specifically, North Dakota’s autonomous vehicle legislation authorizes full deployment with or without a human operator, contrasting with more restrictive approaches in states like California and New York [107]. The lack of standardized federal regulations for testing and deploying autonomous farm vehicles hinders cross-state operations and discourages investment in this technology.

Social acceptance remains a significant issue as rural communities contend with apprehensions around labor displacement and distrust towards autonomous systems [83,88]. Environmental factors, such as the energy consumption of autonomous technology and the emissions generated during manufacturing, hinder the sustainable implementation of these technologies [19,108]. Moreover, deficient rural infrastructure and limited farmer training hinder smooth incorporation into current activities. Addressing these problems requires a collaborative approach that incorporates technological innovation, federal regulatory alignment, economic incentives, and community involvement to ensure the responsible and equitable use of autonomous truck systems in agriculture.

4.4. Future Development of Autonomous Trucking

The future of autonomous trucking in agriculture is poised to be transformative, driven by technological advancements and evolving industry needs. As demand for agricultural efficiency grows, autonomous trucking technologies are poised to address ongoing challenges, including labor shortages, logistical bottlenecks, and rising transportation costs [109,110]. North Dakota’s pilot programs, such as the Minn-Dak Farmers Cooperative’s leader-follower platooning system, offer a glimpse of this future [6]. These initiatives demonstrate how automation can improve reliability and operational efficiency, particularly for repetitive, short-haul routes in rural settings [111,112].

As presented in Figure 8, the future advancement of autonomous trucks will depend on advanced communication systems, instantaneous data processing, and flawless interoperability across vehicles, infrastructure, and decision-making platforms [113]. Critical technologies, such as emergency detection algorithms, RFID systems, and cellular networks, will enhance safety, facilitate regulatory compliance, and improve operational efficiency. Standardized communication protocols and strong cybersecurity safeguards will be essential for the robustness and scalability of autonomous transportation systems. As 5G and edge computing converge, these developments will enable faster and more reliable responses, resulting in an ecosystem that supports the safe and efficient deployment of autonomous trucks across diverse conditions.

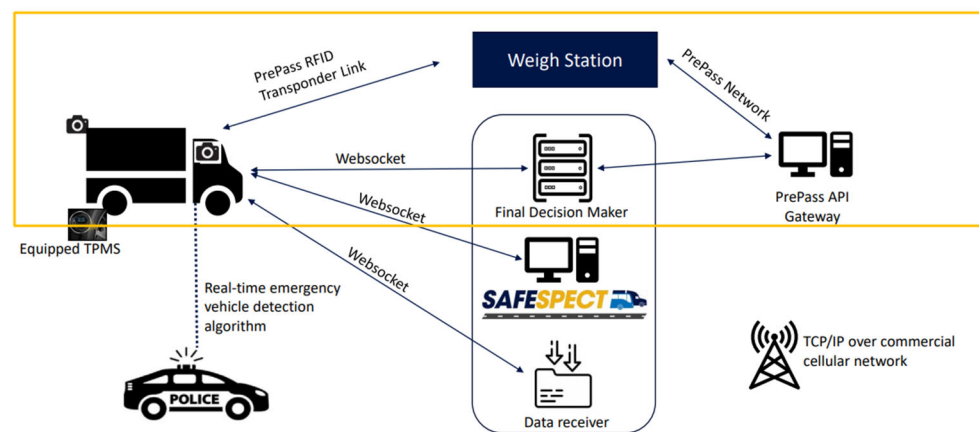


Figure 8. High-level logical architecture of autonomous truck systems [33].

A significant aspect of future development is the technological advancements that enhance the versatility, efficiency, and accessibility of autonomous trucks. Adopting retrofit kits, such as those developed by Kratos Defense, enables traditional trucks to be converted into autonomous vehicles without necessitating costly fleet replacement [34]. These bolt-on systems include RTK GPS, obstacle detection sensors, and encrypted V2V communication, ensuring precise navigation and operational safety even in GPS-degraded environments. The modularity of these systems enables farmers to transfer them between vehicles, extending the life cycle of automation investments and reducing upfront costs.

Moreover, advancements in V2X communication are expected to be pivotal in the next phase of AV deployment [87]. This technology enables seamless interaction among autonomous trucks, infrastructure, and other road users, facilitating more coordinated and efficient transportation systems. According to Raj Bridgelall [87], implementing V2X could significantly reduce fuel consumption and improve traffic flow, especially in rural areas where traditional infrastructure often struggles to support modern transportation needs. These advancements, combined with improvements in battery technology for electric autonomous vehicles (AVs), further align autonomous trucking with the agricultural industry's goals of sustainability and reduced environmental impact.

Although the prospects are favorable, obstacles persist. Policy reform and public acceptance will be crucial in determining the rate of adoption. Legislative updates are needed to enable broader deployment of fully autonomous trucks in North Dakota and other rural states, where regulations limit operations to specific highways or require a safety driver onboard. Additionally, fostering trust in technology through public education and stakeholder engagement will be crucial, especially among rural and tribal communities that may perceive AVs as a threat to traditional jobs [88,114]. Ultimately, the effective integration of autonomous trucking into agriculture will depend on the incorporation of cutting-edge technological innovations and collaborative efforts among policymakers, industry leaders, and agricultural stakeholders. These developments position autonomous vehicles to transform agricultural logistics, ensuring North Dakota leads in technical innovation while addressing the increasing demands of a global food system.

4.5. Policy and Research Implications

The transformative potential of autonomous truck systems within North Dakota's agricultural supply chain necessitates the establishment of coordinated policy frameworks that effectively address the fragmented regulatory landscape present across various states in the United States. This is particularly pertinent considering that agricultural supply networks inherently extend across multiple jurisdictions. As illustrated in Figure 9, the patchwork of state-level regulations creates operational complexity for agricultural operators whose grain, livestock, and crop transportation routes cross state boundaries. North Dakota's progressive stance, explicitly permitting autonomous truck testing and deployment since 2019, demonstrates the importance of clear regulatory frameworks in fostering agricultural logistics innovation [34]. However, federal policy coordination is essential to establish standardized guidelines specifically addressing autonomous truck operations in agriculture, including protocols for farm-to-market transportation, cross-state grain hauling, and seasonal deployment patterns unique to agricultural supply chains. The TRL analysis reveals that regulatory uncertainty particularly impacts TRL 6–7 technologies, such as autonomous docking systems for grain elevators and advanced sensor fusion technologies for agricultural route optimization, which require clear safety standards and certification processes before widespread deployment in agricultural supply chains.

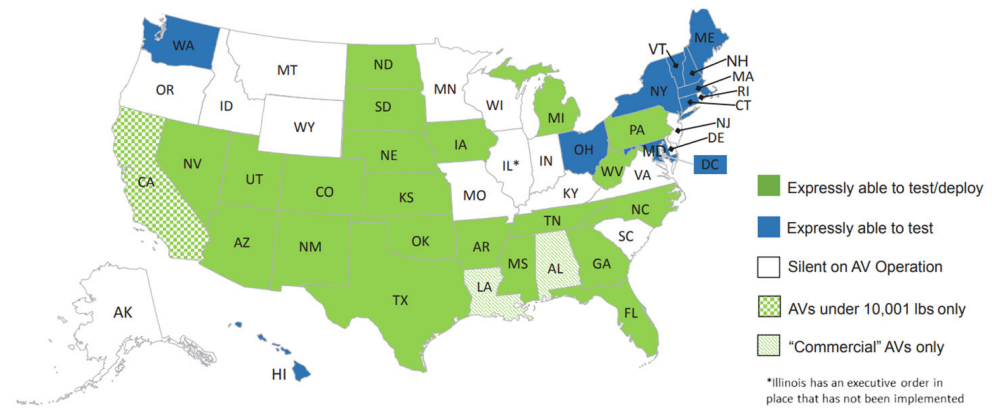


Figure 9. State AV laws and regulations [115].

Moreover, strategic infrastructure investments aligned with technology readiness levels are crucial for enabling autonomous truck systems to enhance North Dakota's agricultural supply chain efficiency. High-readiness technologies (TRL 8–9), such as GPS/RTK positioning and V2V communication systems, can achieve immediate deployment benefits through targeted enhancements to agricultural transportation corridors. These enhancements include expanded broadband connectivity for rural grain elevators, improved road markings on farm-to-market routes, and communication infrastructure supporting vehicle-to-infrastructure systems at processing facilities. For development-phase technologies (TRL 4–6), infrastructure investments should focus on creating agricultural-specific testbeds that address North Dakota's unique supply chain challenges, particularly in cold-weather testing facilities where autonomous trucks can validate their winter operations capabilities, essential for year-round grain transportation and livestock hauling. Public–private partnerships should establish dedicated testing corridors connecting farms, grain elevators, and processing facilities, generating real-world performance data essential for advancing autonomous truck technologies from TRL 4–6 to commercial readiness in agricultural supply chain applications.

Additionally, research funding priorities should target critical technology gaps identified in the TRL analysis, with particular emphasis on advancing autonomous truck systems from development phases to commercial deployment in agricultural supply chain operations. Cold-weather operations research represents the highest priority for North Dakota's agricultural transportation division, as current systems demonstrate limited effectiveness in extreme winter conditions where temperatures reach -30°F , presenting significant challenges for autonomous trucks transporting grain, livestock, and agricultural inputs across the state's vast supply network. Hence, research investments should focus on developing winterized sensor packages, advanced heating systems for critical components, and AI algorithms specifically adapted to navigate snow and ice conditions safely while maintaining supply chain reliability. Additionally, terrain-adaptive navigation systems require focused research investment to enable autonomous truck operations beyond structured highways, particularly for farm-to-elevator transportation on unpaved rural roads and the variable terrain characteristic of agricultural environments. Human-automation interaction research is crucial for addressing social acceptance challenges in rural communities, investigating optimal models for collaboration between autonomous trucks and agricultural workers, and developing workforce transition strategies that position autonomous systems as tools that enhance human capabilities rather than replace agricultural employment.

Economic policy mechanisms should address the high capital costs that present adoption barriers for small and medium-sized agricultural operations seeking to integrate autonomous trucks into their supply chain operations. Targeted financial incentives, in-

cluding tax credits for the adoption of autonomous trucks in agricultural applications and cooperative ownership models that leverage North Dakota's strong agricultural cooperative tradition, represent promising approaches for sharing technology costs among multiple farming operations while transforming supply chain efficiency. Policy support should include regulatory flexibility for shared autonomous truck fleets serving multiple agricultural cooperatives, financing assistance for cooperative technology investments, and technical assistance for developing collaborative autonomous transportation programs that optimize grain hauling, livestock transportation, and agricultural input delivery across the state's extensive farming regions. Research and development tax credits should specifically target technologies at TRL 4–6 critical for agricultural applications, encouraging private sector investment in autonomous truck systems designed for agricultural supply chain optimization. This support will also facilitate field testing and validation activities, which are essential for advancing technology readiness levels in real-world agricultural operations. By aligning policy frameworks with technology readiness levels, prioritizing agricultural supply chain-specific research gaps, and addressing economic barriers through cooperative models, North Dakota can position itself as a leader in agricultural innovation, ensuring that autonomous truck systems contribute to a sustainable, efficient, and economically viable transformation of the agricultural supply chain.

5. Conclusions and Future Directions

This comprehensive study provides a theoretical understanding of agricultural technology adoption by demonstrating how the SETS framework provides superior analytical power for understanding complex innovation adoption processes. The systematic integration of SETS with TRL assessment reveals critical mechanistic insights: technological maturity operates as a mediating variable between system capabilities and adoption barriers, where higher TRLs (8–9) significantly reduce implementation complexity across social and environmental dimensions. The analysis reveals that autonomous truck adoption follows a predictable pattern, where technological system advancements systematically influence social system receptivity through three interconnected pathways: trust formation influenced by observable technology performance, economic utility perception shaped by demonstrated cost–benefit ratios, and cultural compatibility determined by alignment with existing agricultural practices. The predominant focus on technological and economic dimensions in the current literature versus limited social change research indicates a misalignment between research priorities and adoption requirements, suggesting that social acceptance operates as a critical gatekeeper mechanism determining whether technologically mature systems achieve practical implementation. The regulatory fragmentation analysis reveals a policy innovation lag mechanism, where technological advancements consistently outpace regulatory adaptation, creating implementation barriers that persist across jurisdictions. This demonstrates how regulatory approaches fundamentally shape technology adoption trajectories through jurisdictional arbitrage effects, where agricultural operations gravitate toward supportive regulatory environments.

The deployment strategy outlines key mechanisms in agricultural technology adoption, where Phase 1 leverages the demonstration effects of high-readiness technologies to create observable benefits, Phase 2 operates through diffusion mechanisms, where early adopter success reduces perceived risks for mainstream operations, and Phase 3 relies on institutional pressure mechanisms to drive adoption among traditionally conservative operators. This progression reflects the adoption pathway dependencies, where each phase creates enabling conditions for subsequent stages, requiring sustained coordination across technological, social, and regulatory dimensions, rather than isolated technology-push strategies. The TRL assessment framework implies a cost-readiness relationship, where

higher TRLs correspond to lower implementation costs and reduced economic risks. This suggests that strategic technology investment should prioritize advancing TRL 4–6 technologies to commercial readiness rather than developing new TRL 1–3 innovations. The systematic analysis identifies critical research frontiers that require immediate attention, particularly cold-weather operational research, which represents the highest priority for North Dakota’s agricultural context. Current TRL 4–6 technologies demonstrate limited effectiveness in extreme weather conditions essential for year-round agricultural operations. Additionally, human-automation interaction research emerges as crucial for addressing social acceptance challenges, requiring an investigation of optimal collaboration models between autonomous systems and agricultural workers that enhance, rather than replace, human capabilities in agricultural operations.

As global agricultural systems confront mounting pressures from labor shortages, climate variability, supply chain disruptions, and sustainability imperatives, autonomous truck systems emerge as a critical pathway toward resilient, efficient, and economically viable agricultural supply chains capable of meeting growing global food security demands. This study’s systematic framework provides stakeholders with evidence-based tools for navigating the complex intersection of technological innovation, social acceptance, regulatory compliance, and economic feasibility that determines the success of autonomous truck adoption. The strategic implementation framework developed through SETS-guided analysis offers agricultural cooperatives, technology developers, and policymakers concrete guidance for coordinating autonomous truck deployment efforts by aligning technological development priorities with social acceptance mechanisms and regulatory evolution pathways. The findings position North Dakota as a potential leader in agricultural autonomous truck innovation, while providing transferable insights for agricultural regions globally seeking to harness the benefits of autonomous technology. This represents more than technological advancement, but embodies a fundamental shift toward precision-driven, data-enabled agricultural systems. The transformation of agricultural supply chains through autonomous truck integration establishes the analytical foundation for realizing this transformative potential through systematic, theoretically grounded, and practically oriented deployment strategies that address the interconnected challenges of technological readiness, social acceptance, regulatory harmonization, and economic accessibility in agricultural innovation adoption.

Accordingly, future research directions should address several critical knowledge gaps identified through this comprehensive analysis, particularly the need for longitudinal empirical studies that validate autonomous truck performance under diverse agricultural conditions and quantitative modeling approaches that provide vigorous cost–benefit assessments for different implementation scenarios. The integration of emerging technologies such as edge computing, 5G connectivity, and advanced sensor fusion presents opportunities for developing next-generation autonomous truck systems capable of operating reliably in unstructured agricultural environments. Additionally, research into human-automation interaction models specific to agricultural contexts is crucial for developing deployment strategies that enhance, rather than replace, human expertise in agricultural operations. The scalability of the findings to other agricultural areas globally represents a significant opportunity for expanding the theoretical and practical contributions of this research. At the same time, the development of standardized evaluation frameworks for autonomous truck technologies in agriculture could facilitate more effective technology transfer and adoption across diverse agricultural contexts. As the agricultural sector continues to confront mounting pressures from labor shortages, climate variability, and sustainability imperatives, the strategic implementation of autonomous truck systems emerges as a critical pathway

toward resilient, efficient, and economically viable agricultural supply chains that can meet the growing demands of global food security.

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References

1. Khayyam, H.; Javadi, B.; Jalili, M.; Jazar, R.N. Artificial Intelligence and Internet of Things for Autonomous Vehicles. In *Nonlinear Approaches in Engineering Applications*; Springer: Cham, Switzerland, 2020; pp. 39–68. [\[CrossRef\]](#)
2. Anderhofstadt, B.; Spinler, S. Preferences for autonomous and alternative fuel-powered heavy-duty trucks in Germany. *Transp. Res. D Transp. Environ.* **2020**, *79*, 102232. [\[CrossRef\]](#)
3. Ren, X.; Huang, B.; Yin, H. A review of the large-scale application of autonomous mobility of agricultural platform. *Comput. Electron. Agric.* **2023**, *206*, 107628. [\[CrossRef\]](#)
4. Maung, T.A.; Gustafson, C.R. The economic feasibility of sugar beet biofuel production in central North Dakota. *Biomass Bioenergy* **2011**, *35*, 3737–3747. [\[CrossRef\]](#)
5. Wang, B.; Zhu, J.; Chai, X.; Liu, B.; Zhang, G.; Yao, W. Research status and development trend of key technology of agricultural machinery chassis in hilly and mountainous areas. *Comput. Electron. Agric.* **2024**, *226*, 109447. [\[CrossRef\]](#)
6. Metzger, M. Autonomous Truck Platooning. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
7. Mousazadeh, H. A technical review on navigation systems of agricultural autonomous off-road vehicles. *J. Terramechanics* **2013**, *50*, 211–232. [\[CrossRef\]](#)
8. Upadhyay, A.; Zhang, Y.; Koparan, C.; Rai, N.; Howatt, K.; Bajwa, S.; Sun, X. Advances in ground robotic technologies for site-specific weed management in precision agriculture: A review. *Comput. Electron. Agric.* **2024**, *225*, 109363. [\[CrossRef\]](#)
9. Prioleau, D.; Dames, P.; Alikhademi, K.; Gilbert, J.E. Barriers to the Adoption of Autonomous Vehicles in Rural Communities. In Proceedings of the 2020 IEEE International Symposium on Technology and Society (ISTAS), New York, NY, USA, 12–15 November 2020; pp. 91–98. [\[CrossRef\]](#)
10. Zhao, J.; Zhao, W.; Deng, B.; Wang, Z.; Zhang, F.; Zheng, W.; Cao, W.; Nan, J.; Lian, Y.; Burke, A.F. Autonomous driving system: A comprehensive survey. *Expert Syst. Appl.* **2024**, *242*, 122836. [\[CrossRef\]](#)
11. Hamilton, R.; Seager, H.; Divakarla, K.P.; Emadi, A.; Razavi, S. Modeling and Simulation of an Autonomous-capable Electrified Vehicle: A Review. In Proceedings of the 2018 IEEE Electrical Power and Energy Conference (EPEC), New York, NY, USA, 10–11 October 2018; pp. 1–7. [\[CrossRef\]](#)
12. Tao, X.; Mårtensson, J.; Warnquist, H.; Pernestål, A. Short-term maintenance planning of autonomous trucks for minimizing economic risk. *Reliab. Eng. Syst. Saf.* **2021**, *220*, 108251. [\[CrossRef\]](#)
13. Babak, S.-J.; Hussain, S.A.; Karakas, B.; Cetin, S. Control of autonomous ground vehicles: A brief technical review. *IOP Conf. Ser. Mater. Sci. Eng.* **2017**, *224*, 012029. [\[CrossRef\]](#)

14. Cugurullo, F.; Acheampong, R.A.; Gueriau, M.; Dusparic, I. The transition to autonomous cars, the redesign of cities and the future of urban sustainability. *Urban Geogr.* **2021**, *42*, 833–859. [CrossRef]
15. Kim, E.; Kim, Y.; Park, J. The Necessity of Introducing Autonomous Trucks in Logistics 4.0. *Sustainability* **2022**, *14*, 3978. [CrossRef]
16. Dougherty, S.; Ellen, P.; Stowell, J.; Richards, A.W. Perceptions of Fully Autonomous Freight Trucks. *SSRN Electron. J.* **2017**. [CrossRef]
17. Gu, Y.; Goez, J.C.; Guajardo, M.; Wallace, S.W. Autonomous vessels: State of the art and potential opportunities in logistics. *Int. Trans. Oper. Res.* **2021**, *28*, 1706–1739. [CrossRef]
18. Theoto, T.N.; Kaminski, P.C. A country-specific evaluation on the feasibility of autonomous vehicles. *Prod. Manag. Dev.* **2019**, *17*, 123–133. [CrossRef]
19. Kassai, E.T.; Azmat, M.; Kummer, S. Scope of Using Autonomous Trucks and Lorries for Parcel Deliveries in Urban Settings. *Logistics* **2020**, *4*, 17. [CrossRef]
20. Mahajan, K.; Masud, S.S.B.; Kondyli, A. Navigating the landscape of automated truck platooning: A systematic review on stakeholder perspectives, employment implications, and regulatory challenges. *Transp. Res. Interdiscip. Perspect.* **2024**, *23*, 101009. [CrossRef]
21. Lardy, G. The Future of Autonomy in Agricultural Production and Marketing. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
22. Kalk, B. How We Achieved Fully Autonomous Operations at Brønnøy Kalk. 2023. Available online: https://www.youtube.com/watch?v=5CesNA_VY4c (accessed on 16 February 2025).
23. Bai, Y.; Zhang, B.; Xu, N.; Zhou, J.; Shi, J.; Diao, Z. Vision-based navigation and guidance for agricultural autonomous vehicles and robots: A review. *Comput. Electron. Agric.* **2023**, *205*, 107584. [CrossRef]
24. Holzinger, A.; Schweier, J.; Gollob, C.; Nothdurft, A.; Hasenauer, H.; Kirisits, T.; Häggström, C.; Visser, R.; Cavalli, R.; Spinelli, R.; et al. From Industry 5.0 to Forestry 5.0: Bridging the gap with Human-Centered Artificial Intelligence. *Curr. For. Rep.* **2024**, *10*, 442–455. [CrossRef]
25. Wang, N.; Li, S.; Xiao, J.; Wang, T.; Han, Y.; Wang, H.; Zhang, M.; Li, H. A collaborative scheduling and planning method for multiple machines in harvesting and transportation operations-Part I: Harvester task allocation and sequence optimization. *Comput. Electron. Agric.* **2025**, *232*, 110060. [CrossRef]
26. Shamshiri, R.R.; Sturm, B.; Weltzien, C.; Fulton, J.; Khosla, R.; Schirrmann, M.; Raut, S.; Basavegowda, D.H.; Yamin, M.; Hameed, I.A. Digitalization of agriculture for sustainable crop production: A use-case review. *Front. Environ. Sci.* **2024**, *12*, 1375193. [CrossRef]
27. Krishnan, R.; Perumal, E.; Govindaraj, M.; Kandasamy, L. *Enhancing Logistics Operations Through Technological Advancements for Superior Service Efficiency*; IGI Global: Hershey, PA, USA, 2024; pp. 61–82. [CrossRef]
28. Feng, S.; Liu, Y.; Pressgrove, I.; Ben-Tzvi, P. Autonomous Alignment and Docking Control for a Self-Reconfigurable Modular Mobile Robotic System. *Robotics* **2024**, *13*, 81. [CrossRef]
29. Olaleye, I.A.; Mokogwu, C.; Olufemi-Phillips, A.Q.; Adewale, T.T. Transforming supply chain resilience: Frameworks and advancements in predictive analytics and data-driven strategies. *Open Access Res. J. Multidiscip. Stud.* **2024**, *8*, 085–093. [CrossRef]
30. Hu, Q.; Gu, W.; Wu, L.; Zhang, L. Optimal autonomous truck platooning with detours, nonlinear costs, and a platoon size constraint. *Transp. Res. E Logist. Transp. Rev.* **2024**, *186*, 103545. [CrossRef]
31. Zhong, X.; Zhang, M.; Tang, T.; Adhikari, B.; Ma, Y. Advances in intelligent detection, monitoring, and control for preserving the quality of fresh fruits and vegetables in the supply chain. *Food Biosci.* **2023**, *56*, 103350. [CrossRef]
32. Salama, R.; Al-Turjman, F. *Smart Grid Environment, Data Security in the Internet of Things, and Supply Chain Ecosystem Transformation*; IGI Global: Hershey, PA, USA, 2024; pp. 305–332. [CrossRef]
33. Routhier, B. FMCSA ADS Safety Research. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
34. Factor, M. Self-Driving Sugarbeet Truck Deployment. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
35. Corcoran, H. Navigating New Roads: A Four-Pillar Framework for Connected & Automated Success in Rural & Tribal Communities. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
36. Jantzi, D. North Dakota Agriculture in One Word–Diverse. U.S. Department of Agriculture. Available online: [https://www.usda.gov/about-usda/news/blog/north-dakota-agriculture-one-word-diverse#:~:text=The%20Peace%20Garden%20State%20sold,Profile%20\(PDF%2C%20920%20KB\)!](https://www.usda.gov/about-usda/news/blog/north-dakota-agriculture-one-word-diverse#:~:text=The%20Peace%20Garden%20State%20sold,Profile%20(PDF%2C%20920%20KB)!) (accessed on 16 February 2025).
37. Mengist, W.; Soromessa, T.; Legese, G. Method for conducting systematic literature review and meta-analysis for environmental science research. *MethodsX* **2020**, *7*, 100777. [CrossRef]
38. Van de Ven, A.H. The innovation journey: You can't control it, but you can learn to maneuver it. *Innovation* **2017**, *19*, 39–42. [CrossRef]

39. Caputo, A.; Kargina, M. A user-friendly method to merge Scopus and Web of Science data during bibliometric analysis. *J. Mark. Anal.* **2022**, *10*, 82–88. [[CrossRef](#)]
40. Echchakoui, S. Why and how to merge Scopus and Web of Science during bibliometric analysis: The case of sales force literature from 1912 to 2019. *J. Mark. Anal.* **2020**, *8*, 165–184. [[CrossRef](#)]
41. Jones, R.; Bridgelall, R.; Tolliver, D. Route Risk Index for Autonomous Trucks. *Appl. Sci.* **2024**, *14*, 2892. [[CrossRef](#)]
42. Bridgelall, R.; Jones, R.; Tolliver, D. Ranking Opportunities for Autonomous Trucks Using Data Mining and GIS. *Geographies* **2023**, *3*, 806–823. [[CrossRef](#)]
43. McPhearson, T.; Cook, E.M.; Barbés-Blázquez, M.; Cheng, C.; Grimm, N.B.; Andersson, E.; Barbosa, O.; Chandler, D.G.; Chang, H.; Chester, M.V.; et al. A social-ecological-technological systems framework for urban ecosystem services. *One Earth* **2022**, *5*, 505–518. [[CrossRef](#)]
44. Chester, M.V.; Miller, T.R.; Muñoz-Erickson, T.A.; Helmrich, A.M.; Iwaniec, D.M.; McPhearson, T.; Cook, E.M.; Grimm, N.B.; Markolf, S.A. Sensemaking for entangled urban social, ecological, and technological systems in the Anthropocene. *npj Urban Sustain.* **2023**, *3*, 39. [[CrossRef](#)]
45. Sharifi, A. Resilience of urban social-ecological-technological systems (SETS): A review. *Sustain. Cities Soc.* **2023**, *99*, 104910. [[CrossRef](#)]
46. Bayar, G.; Bergerman, M.; Koku, A.B.; Konukseven, E.I. Localization and control of an autonomous orchard vehicle. *Comput. Electron. Agric.* **2015**, *115*, 118–128. [[CrossRef](#)]
47. Badgujar, C.; Das, S.; Figueroa, D.M.; Flippo, D.; Welch, S. Deep neural networks to predict autonomous ground vehicle behavior on sloping terrain field. *J. Field Robot.* **2023**, *40*, 919–933. [[CrossRef](#)]
48. Guo, L.-S.; Zhang, Q. A low-cost integrated positioning system for autonomous off-highway vehicles. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2008**, *222*, 1997–2009. [[CrossRef](#)]
49. Liu, X.; Chen, S.W.; Nardari, G.V.; Qu, C.; Cladera, F.; Taylor, C.J.; Kumar, V. Challenges and Opportunities for Autonomous Micro-UAVs in Precision Agriculture. *IEEE Micro* **2022**, *42*, 61–68. [[CrossRef](#)]
50. Zha, J.; Yang, T.; Mueller, M.W. Agri-fly: Simulator for Uncrewed Aerial Vehicle Flight in Agricultural Environments. *IEEE Access* **2024**, *12*, 140900–140907. [[CrossRef](#)]
51. Durand-Petiteville, A.; Le Flecher, E.; Cadenat, V.; Sentenac, T.; Vougioukas, S. Tree Detection with Low-Cost Three-Dimensional Sensors for Autonomous Navigation in Orchards. *IEEE Robot. Autom. Lett.* **2018**, *3*, 3876–3883. [[CrossRef](#)]
52. Badgujar, C.; Flippo, D.; Welch, S. Artificial neural network to predict traction performance of autonomous ground vehicle on a sloped soil bin and uncertainty analysis. *Comput. Electron. Agric.* **2022**, *196*, 106867. [[CrossRef](#)]
53. Hunter, J.E.; Gannon, T.W.; Richardson, R.J.; Yelverton, F.H.; Leon, R.G. Integration of remote-weed mapping and an autonomous spraying unmanned aerial vehicle for site-specific weed management. *Pest Manag. Sci.* **2020**, *76*, 1386–1392. [[CrossRef](#)] [[PubMed](#)]
54. Badgujar, C.M.; Flippo, D.; Brokesh, E.; Welch, S. Experimental Investigation on Traction, Mobility, and Energy Usage of a Tracked Autonomous Ground Vehicle on a Sloped Soil Bin. *J. ASABE* **2022**, *65*, 835–847. [[CrossRef](#)]
55. Mack, E.A.; Miller, S.R.; Chang, C.-H.; Van Fossen, J.A.; Cotten, S.R.; Savolainen, P.T.; Mann, J. The politics of new driving technologies: Political ideology and autonomous vehicle adoption. *Telemat. Inform.* **2021**, *61*, 101604. [[CrossRef](#)]
56. Faryadi, S.; Velni, J.M. A reinforcement learning-based approach for modeling and coverage of an unknown field using a team of autonomous ground vehicles. *Int. J. Intell. Syst.* **2021**, *36*, 1069–1084. [[CrossRef](#)]
57. Bell, T.W.; Nidzieko, N.J.; Siegel, D.A.; Miller, R.J.; Nelson, N.B.; Reed, D.C.; Fedorov, D.; Moran, C.; Snyder, J.N.; Cavanaugh, K.C.; et al. The Utility of Satellites and Autonomous Remote Sensing Platforms for Monitoring Offshore Aquaculture Farms: A Case Study for Canopy Forming Kelps. *Front. Mar. Sci.* **2020**, *7*, 520223. [[CrossRef](#)]
58. Neupane, J.; Maja, J.M.; Miller, G.; Marshall, M.; Cutulle, M.; Luo, J. Effect of Controlled Defoliant Application on Cotton Fiber Quality. *Appl. Sci.* **2023**, *13*, 5694. [[CrossRef](#)]
59. Nogueira, E.A.; Rocha, B.M.; Vieira, G.d.S.; da Fonseca, A.U.; Felix, J.P.; Oliveira, A.; Soares, F. Enhancing Corn Image Resolution Captured by Unmanned Aerial Vehicles with the Aid of Deep Learning. *IEEE Access* **2024**, *12*, 149090–149098. [[CrossRef](#)]
60. Rounsaville, J.D.; Dvorak, J.S.; Stombaugh, T.S. Methods for Calculating Relative Cross-Track Error for ASABE/ISO Standard 12188-2 from Discrete Measurements. *Trans. ASABE* **2016**, *59*, 1609–1616. [[CrossRef](#)]
61. Badgujar, C.M.; Wu, H. Flippo, and E. Brokesh. Design, Fabrication, and Experimental Investigation of Screw Auger Type Feed Mechanism for a Robotic Wheat Drill. *J. ASABE* **2022**, *65*, 1333–1342. [[CrossRef](#)]
62. Li, N.; Remeikas, C.; Xu, Y.; Jayasuriya, S.; Ehsani, R. Task Assignment and Trajectory Planning Algorithm for a Class of Cooperative Agricultural Robots. *J. Dyn. Syst. Meas. Control* **2015**, *137*, 4028849. [[CrossRef](#)]
63. Deka, S.A.; Lee, D.; Tomlin, C.J. Towards Cyber-Physical Systems Robust to Communication Delays: A Differential Game Approach. *IEEE Control Syst. Lett.* **2022**, *6*, 2042–2047. [[CrossRef](#)]
64. Carrière, O.; Hermand, J.-P. Sequential Bayesian geoacoustic inversion for mobile and compact source-receiver configuration. *J. Acoust. Soc. Am.* **2012**, *131*, 2668–2681. [[CrossRef](#)] [[PubMed](#)]

65. Chi, G.; Wang, D.; Hagedorn, A.D. Future interstate highway system demands: Predictions based on population projections. *Case Stud. Transp. Policy* **2019**, *7*, 384–394. [CrossRef] [PubMed]
66. Bridgelall, R. Spatial Analysis of Middle-Mile Transport for Advanced Air Mobility: A Case Study of Rural North Dakota. *Sustainability* **2024**, *16*, 8949. [CrossRef]
67. Krank, J. Robo-Crop: The Imminence of Autonomous Technology in Agriculture. 2020. Available online: https://heinonline.org/HOL/Page?collection=journals&handle=hein.journals/dragl25&id=497&men_tab=srchresults (accessed on 8 December 2024).
68. Etezadi, H.; Eshkabilov, S. A Comprehensive Overview of Control Algorithms, Sensors, Actuators, and Communication Tools of Autonomous All-Terrain Vehicles in Agriculture. *Agriculture* **2024**, *14*, 163. [CrossRef]
69. Talebian, A.; Mishra, S. Unfolding the state of the adoption of connected autonomous trucks by the commercial fleet owner industry. *Transp. Res. E Logist. Transp. Rev.* **2022**, *158*, 102616. [CrossRef]
70. Uddin, M. Factors Influencing Adoption and Adoption Intensity of Precision Agriculture Technologies in South Dakota. Master's Thesis, South Dakota State University, Brookings, SD, USA, 2020. Available online: <https://www.proquest.com/docview/2455823975?pq-origsite=gscholar&fromopenview=true&sourcetype=Dissertations%20%20Theses> (accessed on 8 December 2024).
71. Du, Y.; Zhang, G.; Tsang, D.; Jawed, M.K. Deep-CNN based Robotic Multi-Class Under-Canopy Weed Control in Precision Farming. In Proceedings of the 2022 International Conference on Robotics and Automation (ICRA), Philadelphia, PA, USA, 23–27 May 2022; pp. 2273–2279. [CrossRef]
72. Fagnant, D.J.; Kockelman, K. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transp. Res. Part A Policy Pract.* **2015**, *77*, 167–181. [CrossRef]
73. Pedersen, S.M.; Fountas, S.; Blackmore, S. Economic potential of robots for high value crops and landscape treatment. In *Precision Agriculture '07*; Brill | Wageningen Academic: Wageningen, The Netherlands, 2007; pp. 457–464. [CrossRef]
74. Sara, G.; Todde, G.; Pinna, D.; Waked, J.; Caria, M. *Implementation and Assessment of an Autonomous Ground Vehicle (AGV) for On-Field Agricultural Operations*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 340–348. [CrossRef]
75. Stock, R.; Gardezi, M. Make bloom and let wither: Biopolitics of precision agriculture at the dawn of surveillance capitalism. *Geoforum* **2021**, *122*, 193–203. [CrossRef]
76. Chen, G. *Advances in Agricultural Machinery and Technologies*; CRC Press: Boca Raton, FL, USA, 2018. [CrossRef]
77. Mirzazadeh, B.; Huang, Y.; Motuba, D. The Attitudes towards Autonomous Vehicles in a Medium-Sized Academic-Dominated U.S. Metropolitan Area with Cold Winters. *Int. J. Hum. Comput. Interact.* **2024**, *40*, 1033–1048. [CrossRef]
78. Pederson, B. A Field Study on LiDAR Sensor for Unmanned Ground Vehicle Navigation Application in Precision Agriculture. Master's Thesis, North Dakota State University, Fargo, ND, USA, 2022. Available online: <https://www.proquest.com/openview/ecaffbcb2208ded27a769465bab3a77f/1?pq-origsite=gscholar&cbl=18750&diss=y> (accessed on 8 December 2024).
79. Duchsherer, C.J. On the Profitability of UAS-Based NDVI Imagery for Variable Rate Nitrogen Prescriptions in Corn and Wheat in North Dakota. Master's Thesis, North Dakota State University, Fargo, ND, USA, 2018. Available online: <https://library.ndsu.edu/ir/items/d90d3e18-b593-4f46-a798-886219d04697> (accessed on 8 December 2024).
80. Niederluecke, K.J.; Tremblay, B.E.; Merrill, R.K.C.; Ewing, S. Protecting Innovation Panel. 2024. Available online: https://law.und.edu/_files/docs/ndlr/pdf/issues/99/3/99ndlr523.pdf (accessed on 9 December 2024).
81. Delavarpour, N. Design and Development of an Automatic Steering System for Agricultural Towed Implements. Ph.D. Thesis, North Dakota State University, Fargo, ND, USA, 2022. Available online: <https://www.proquest.com/docview/2669532489?pq-origsite=gscholar&fromopenview=true&sourcetype=Dissertations%20%20Theses> (accessed on 8 December 2024).
82. Dooley, F.J. A Comprehensive Review and the Proposed Reorganization of North Dakota State Government Transportation Agencies (DP-65). 1988. Available online: https://rosap.ntl.bts.gov/view/dot/59801/dot_59801_DS1.pdf (accessed on 8 December 2024).
83. Mirzazadeh, B. The Acceptance of Autonomous Vehicles and Their Impacts on Travel Behavior for an Academic Subpopulation in a Midsize U.S. Metropolitan Area with Extremely Cold Winters. Ph.D. Thesis, North Dakota State University, Fargo, ND, USA, 2022. Available online: <https://www.proquest.com/docview/2699970944?pq-origsite=gscholar&fromopenview=true&sourcetype=Dissertations%20%20Theses> (accessed on 8 December 2024).
84. Bishop, R. Our Future with Autonomous Trucking. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
85. Sova, J. Enhanced Inspection Program for ADS vehicles. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
86. Buchhiltz, R. Innovation for Transportation Systems. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
87. Bridgelall, R. Digital Infrastructure: Planning for Autonomous Vehicles. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.
88. Hall, R. Engagement with Tribal Communities. In *Autonomous Trucking in North Dakota: Prospects and Challenges*; Upper Great Plains Transportation Institute: Bismarck, ND, USA, 2024.

89. Hasiri, A.; Kermanshah, A. Exploring the Role of Autonomous Trucks in Addressing Challenges within the Trucking Industry: A Comprehensive Review. *Systems* **2024**, *12*, 320. [CrossRef]
90. Sindi, S.; Woodman, R. Implementing commercial autonomous road haulage in freight operations: An industry perspective. *Transp. Res. Part A Policy Pract.* **2021**, *152*, 235–253. [CrossRef]
91. Helmick, D.; Angelova, A.; Matthies, L. Terrain Adaptive Navigation for planetary rovers. *J. Field Robot.* **2009**, *26*, 391–410. [CrossRef]
92. Wang, R.; Li, Y.; Ma, T.; Chen, Y. Initial Positioning of Terrain Relative Navigation Under Pseudo-Peaks Interference. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 8506916. [CrossRef]
93. Domínguez, M.; Fuertes, J.J.; Reguera, P.; Díaz, I.; Cuadrado, A.A. Internet-based remote supervision of industrial processes using self-organizing maps. *Eng. Appl. Artif. Intell.* **2007**, *20*, 757–765. [CrossRef]
94. Papadimitriou, E.; Schneider, C.; Tello, J.A.; Damen, W.; Vrouenraets, M.L.; Broeke, A.T. Transport safety and human factors in the era of automation: What can transport modes learn from each other? *Accid. Anal. Prev.* **2020**, *144*, 105656. [CrossRef]
95. Zhao, J.; Lee, J.Y. Effect of Connected and Autonomous Vehicles on Supply Chain Performance. *Transp. Res. Rec. J. Transp. Res. Board.* **2023**, *2677*, 402–424. [CrossRef]
96. ESA. The ESA Science Technology Development Route. Sci-ft. Available online: <https://sci.esa.int/web/sci-ft/-/50124-technology-readiness-level> (accessed on 29 June 2025).
97. EU. *Europe 2020 Flagship Initiative Innovation Union: SEC(2010) 1161, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions*; EU Publications: Luxembourg, 2011. [CrossRef]
98. Vik, J.; Melås, A.M.; Stræte, E.P.; Søråa, R.A. Balanced readiness level assessment (BRLa): A tool for exploring new and emerging technologies. *Technol. Forecast. Soc. Chang.* **2021**, *169*, 120854. [CrossRef]
99. ISO 16290:2013; Space Systems—Definition of the Technology Readiness Levels (TRLs) and Their Criteria of Assessment. International Electrotechnical Commission: Geneva, Switzerland, 2024. Available online: <https://www.iso.org/standard/56064.html> (accessed on 29 June 2025).
100. Gunderson, D. Ag Industry Testing Driverless Trucks to Solve Labor Shortage | MPR News. Minnesota Public Radio. Available online: <https://www.mprnews.org/story/2023/11/16/ag-industry-testing-driverless-trucks-to-solve-labor-shortage> (accessed on 29 June 2025).
101. Chiao, D. *Autonomous Vehicles Moving Forward: Perspectives from Industry Leaders*; McKinsey & Company: New York, NY, USA, 2024. Available online: <https://www.mckinsey.com/features/mckinsey-center-for-future-mobility/our-insights/autonomous-vehicles-moving-forward-perspectives-from-industry-leaders> (accessed on 29 June 2025).
102. Heineke, K.; Heuss, R.; Kelkar, A.; Kellner, M. What's Next for Autonomous Vehicles? | McKinsey. McKinsey & Company. Available online: <https://www.mckinsey.com/features/mckinsey-center-for-future-mobility/our-insights/whats-next-for-autonomous-vehicles> (accessed on 29 June 2025).
103. Andrei, N.; Scarlat, C.; Ioanid, A. Transforming E-Commerce Logistics: Sustainable Practices through Autonomous Maritime and Last-Mile Transportation Solutions. *Logistics* **2024**, *8*, 71. [CrossRef]
104. Nitsche, B. Exploring the Potentials of Automation in Logistics and Supply Chain Management: Paving the Way for Autonomous Supply Chains. *Logistics* **2021**, *5*, 51. [CrossRef]
105. Bronson, K. Looking through a responsible innovation lens at uneven engagements with digital farming. *NJAS Wagening. J. Life Sci.* **2019**, *90–91*, 1–6. [CrossRef]
106. Araújo, S.O.; Peres, R.S.; Barata, J.; Lidon, F.; Ramalho, J.C. Characterising the Agriculture 4.0 Landscape—Emerging Trends, Challenges and Opportunities. *Agronomy* **2021**, *11*, 667. [CrossRef]
107. CAD. US—Testing Infrastructure and Procedure Description. Connected and Automated Driving.eu. Available online: <https://www.connectedautomateddriving.eu/regulation-and-policies/national-level/non-eu/us/> (accessed on 1 July 2025).
108. Teleki, A.-C.; Fritz, M.; Kreimeyer, M. *Use Cases for Automated Driving Commercial Vehicles*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 187–200. [CrossRef]
109. McPeak, M. How Self-Driving Trucks Curtail the Driver Shortage. Food Logistics. Available online: <https://www.foodlogistics.com/transportation/trucking/article/22865529/hale-trailer-how-selfdriving-trucks-curtail-the-driver-shortage> (accessed on 17 February 2025).
110. Schuster, A.M.; Agrawal, S.; Britt, N.; Sperry, D.; Van Fossen, J.A.; Wang, S.; Mack, E.A.; Liberman, J.; Cotten, S.R. Will automated vehicles solve the truck driver shortages? Perspectives from the trucking industry. *Technol. Soc.* **2023**, *74*, 102313. [CrossRef]
111. Engesser, V.; Rombaut, E.; Vanhaverbeke, L.; Lebeau, P. Autonomous Delivery Solutions for Last-Mile Logistics Operations: A Literature Review and Research Agenda. *Sustainability* **2023**, *15*, 2774. [CrossRef]
112. Ukoba, K.; Olatunji, K.O.; Adeoye, E.; Jen, T.-C.; Madyira, D.M. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy Environ.* **2024**, *35*, 3833–3879. [CrossRef]

113. Jain, S.; Ahuja, N.J.; Srikanth, P.; Bhadane, K.V.; Nagaiah, B.; Kumar, A.; Konstantinou, C. Blockchain and Autonomous Vehicles: Recent Advances and Future Directions. *IEEE Access* **2021**, *9*, 130264–130328. [[CrossRef](#)]
114. Waltermann, J.; Henkel, S. Public discourse on automated vehicles in online discussion forums: A social constructionist perspective. *Transp. Res. Interdiscip. Perspect.* **2023**, *17*, 100743. [[CrossRef](#)]
115. AVIA. State of AV 2024. 2024. Available online: https://cdn.prod.website-files.com/67ee365c25e6530594bd40c2/684b318f289049a3a648e077_2024%20state%20of%20av-compressed.pdf (accessed on 9 December 2024).

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