Artificial Intelligence in Transportation

Final Report

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16. Abstract
This research provides a strategic assessment of how Artificial Intelligence (AI) can be effectively integrated into the operations of the Wisconsin Department of Transportation (WisDOT). The purpose of the research is to identify key opportunities, challenges, and implementation pathways for AI across six major transportation domains: asset management, safety, operations, digital twin, autonomous vehicles, and generative AI. The research employed a mixed-methods approach, including a comprehensive literature review, a nationwide stakeholder survey, and expert interviews with professionals from public agencies and industry. The findings reveal substantial differences in AI perception between agency and non-agency stakeholders, highlight asset management and operations as near-term priorities, and identify critical barriers such as data fragmentation and workforce readiness. The research introduces a phased AI implementation roadmap and offers tailored recommendations under three time periods: short-term, medium-term, and long-term. These results provide recommendations to WisDOT in prioritizing high-impact, low-risk AI applications in the short term, while laying the groundwork for advanced, system-wide AI integration in the future.

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EXECUTIVE SUMMARY

Background

Artificial Intelligence (AI) has emerged as a transformative force in transportation, enabling smarter, safer, and more efficient systems. However, integrating AI into transportation agency operations requires a strategic understanding of current capabilities, stakeholder perceptions, data readiness, and implementation risks. This study aims to address these gaps by providing a comprehensive, stakeholder-informed roadmap for advancing AI deployment across WisDOT's operations.

Objectives

- Map the current and potential applications of AI in six major transportation domains: Asset Management, Transportation Safety, Traffic Operations, Digital Twin, Autonomous Vehicles, and Generative AI.
- Understand the perceptions, expectations, and concerns about AI from diverse stakeholder groups, particularly state agencies and academic/industry experts.
- Identify key challenges, including data quality, skill gaps, and institutional trust, that affect AI readiness.

Research Approach

To meet these objectives, the study adopted a multi-method approach:

- **Literature Review**: A systematic review of national and international efforts related to AI in transportation.
- **Stakeholder Survey**: A structured survey was distributed to over 100 transportation professionals across public agencies, academia, and private industry.
- **Expert Interviews**: In-depth follow-up interviews were conducted with experts from state DOTs and engineering firms.
- **AI Maturity Mapping**: Perception-based assessments were used to evaluate AI applications in terms of data quality, implementation timeline, risk-benefit balance, and trustworthiness.

Key Findings

- **Divergence in Perceptions**: State agencies prioritize trustworthiness and practical implementation, while academic stakeholders focus more on innovation and technical readiness.

- **Application Maturity**: Among the six AI domains, Asset Management and Operations show the highest perceived readiness and return on investment, while Digital Twin and Generative AI are recognized for their long-term potential but currently face higher uncertainty.
- **Barriers to Implementation**:
  - Data fragmentation and lack of standardized formats.
  - Insufficient AI training and workforce development.
  - Lack of inter-agency collaboration mechanisms.
- **Benefit-Risk Tradeoffs**: High-benefit applications like safety analytics are also associated with higher perceived risk, especially regarding public trust and ethical concerns.

Conclusions and Implementable Recommendations

This research reveals that while AI is advancing rapidly in the broader transportation sector, its adoption by public agencies remains in relatively early stages. Significant opportunities for these agencies lie in Asset Management, Safety, and Traffic Operations, which offer the best near-term benefits. Key challenges include data quality and management, alongside notable skills gaps in the workforce.

The research makes the following prioritized recommendations to WisDOT:

1. **Establish robust data governance** to ensure data quality and standardization.
2. **Prioritize initial AI deployments** in Asset Management, Safety, and Operations due to their high benefit and shorter implementation timelines.
3. **Implement tiered AI training programs** to address identified workforce skill gaps.
4. **Develop clear AI governance policies** to ensure trustworthy, responsible, and ethical AI.
5. **Pursue a diversified partnership strategy** to leverage external expertise and resources.

A phased implementation roadmap is proposed:

- **Short-term (1–3 years)**: Focus on foundational steps such as improving data infrastructure, deploying proven AI tools (e.g., for asset monitoring), and building internal capacity through training and pilot programs.
- **Medium-term (4–7 years)**: Scale successful use cases, expand to complex systems such as real-time operations management, and enhance inter-agency collaboration.
- **Long-term (8+ years)**: Pursue integration of advanced AI systems, including predictive digital twins, autonomous infrastructure readiness, and generative AI applications.

While this study provides a strategic framework, detailed financial planning for specific AI investments (e.g., dollar amounts or budget allocation) was beyond its scope. Looking ahead, a suggested Phase II project would build directly on these findings. Key activities would include conducting in-depth case studies for high-priority use cases, expanding data collection (internally from WisDOT operations and externally from vendors, other agencies, and other states), developing initial AI prototypes, co-designing a workforce development roadmap, and refining the implementation plan with detailed, year-by-year actions and investment scenarios. This next phase would aim to translate the strategic vision into concrete, operational steps for WisDOT's AI adoption journey.

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1. INTRODUCTION

Artificial Intelligence (AI) has rapidly emerged as one of the most transformative technologies, reshaping numerous industries by enabling machines to simulate human intelligence. AI's ability to learn from data, recognize patterns, and make decisions has led to its application across a range of sectors, including finance, healthcare, and national security. Specifically, its potential to revolutionize transportation offers solutions to long-standing challenges, including traffic congestion, crashes, and operational inefficiencies. Transportation is becoming increasingly complex due to growing urbanization, higher vehicle volumes, and evolving mobility needs. However, traditional transportation network management methods, such as manual traffic monitoring and infrastructure maintenance, are no longer sufficient to meet these demands. AI's advancement over the past decade, driven by advancements in machine learning (ML), big data, and computational power, has offered new possibilities for optimizing transportation.

AI's integration into transportation has led to a range of successful applications, from traffic management and safety analysis to infrastructure maintenance and autonomous vehicles. Key areas where AI has demonstrated significant potential include transportation asset management, transportation safety, transportation operations, digital twins, autonomous vehicles, and generative AI. The U.S. Department of Transportation (USDOT), in collaboration with the Federal Highway Administration (FHWA), Federal Railroad Administration (FRA), and Federal Aviation Administration (FAA), has started exploring AI's potential within the transportation ecosystem. For example, the FAA collaborates with government, industry, and academia to develop regulations and standards for drone operations through comprehensive research, supporting safe drone integration. The FHWA awarded a $4.9 million grant to the Delaware DOT for the AI Integrated Transportation Management System (AIITMS). AIITMS analyzes high-resolution data from various sources to manage traffic and generate real-time congestion solutions. The FRA is also advancing the use of AI in transportation by investing in ML and computer vision technologies to enhance railroad safety, such as developing autonomous inspection technologies. These efforts seek to enhance the precision and efficiency of railway inspections, contributing to greater safety and reliability in the railroad industry.

AI's role in transportation is still evolving with undeniable potential. As the USDOT and state transportation agencies continue to explore and implement AI-based solutions, it is necessary to focus on valuable applications that can deliver transformative benefits. By integrating AI into safety-critical domains and optimizing transportation operations, AI can help address some of the most pressing challenges facing transportation today, including congestion, safety, and sustainability. However, it is crucial to adopt a strategic approach to AI deployment, ensuring that stakeholders are well-informed about AI's capabilities and limitations. This project aims to address three interconnected challenges:

1. Mapping the current landscape of AI deployment in transportation across six application domains—Transportation Asset Management, Transportation Safety, Transportation Operations, Digital Twins, Autonomous Vehicles, and Generative AI;
2. Understanding the variation in perceived benefits, risks, and readiness among key stakeholder groups, especially between public sector agencies and academic/research institutions; and
3. Informing the strategic planning and implementation roadmap for the Wisconsin Department of Transportation (WisDOT) and other agencies through evidence-based insights into user perceptions, benefit-risk tradeoffs, and priority areas for investment.

To achieve this, we conducted a targeted literature review, collected perception data through a structured survey and follow-up interview, and performed a cross-sectional analysis of professional attitudes toward AI deployment. Key dimensions of analysis included data quality and availability, perceived benefit-risk balance, application maturity, time investment expectations, and organizational perspectives. The results highlight areas of alignment and divergence among transportation professionals and reveal how experience, institutional affiliation, and domain maturity shape attitudes toward AI.

2. LITERATURE REVIEW

To provide a structured and comprehensive understanding of the state of the practice, the literature was categorized into six representative groups based on their relevance to current agency priorities and future innovation potential: Transportation Asset Management, Transportation Safety, Transportation Operations, Autonomous Vehicles, Digital Twins, and Generative AI. These categories reflect both well-established domains of application and emerging areas that are poised to transform transportation planning, management, and service delivery. Each category is reviewed in detail to summarize the latest technical advances, key use cases, and operational considerations, along with a discussion of practical limitations that agencies must address for effective deployment. A complete and comprehensive literature review is provided in Appendix A.

2.1. Transportation Asset Management

AI enhances asset management by improving decision-making and resource allocation. AI tools are developed for tasks such as automated assessments of pavements and bridges, real-time data analysis, and predictive maintenance [1], [2]. For instance, AI techniques like computer vision, deep learning, and machine learning are used to detect defects like cracks or corrosion [4], [8], predict asset maintenance needs [11], and analyze images of road markings [9], [10]. Additionally, AI can forecast future asset conditions by analyzing historical data and supporting proactive maintenance strategies [13]. DOTs have used AI for automatic pavement condition assessments [3], [7], bridge inspections [14], [15], and roadway geometry analysis [12]. AI automates data collection and analysis, speeds up inspections, improves accuracy, and minimizes human error [5], [6]. AI's predictive capabilities help transportation agencies allocate resources more effectively. By reducing the need for manual inspections, AI enhances safety, especially in hard-to-reach or dangerous areas [16]. For example, the Texas Department of Transportation (TxDOT), in collaboration with the University of Houston, expanded its Transportation Asset Management Plan (TAMP) to include signage and signal assets, leveraging AI for automated condition assessment and prediction. However, implementing AI in asset management faces challenges. For instance, limited access to high-quality data impacts the accuracy of AI systems [17]. Additionally, agencies need to train staff in AI and advanced data analysis. Another issue is the reliability of sensors, which can provide inaccurate data or lack sufficient coverage.

2.2. Transportation Safety

AI applications in transportation safety encompass many innovative applications, including crash prediction systems, VRU monitoring, roadside hazard assessment, road hazard detection, and driver monitoring [18]-[20]. Key AI methods in this field are computer vision, reinforcement learning, statistical learning, deep learning, and machine learning [21]-[23]. These techniques enable systems to process data, learn from experiences, recognize patterns, and continuously improve safety [24], [25]. AI enhances hazard detection, enables real-time interventions, and offers cost-effective solutions by utilizing existing infrastructure [26]-[28]. Moreover, AI improves understanding of crash scenarios [29], [30], aids in prioritizing safety measures [31], [32], and contributes to overall road safety and traffic management improvements [33], [34]. For instance, the Hawaii Department of Transportation (HDOT) participated in the Intersection Safety Challenge by deploying AI-based image recognition systems to detect vulnerable road users (VRUs) and enhance early warning capabilities. However, implementing AI in transportation safety comes with certain costs and potential risks [35]-[40]. These include data quality issues, the need for extensive testing to prevent false detections, high computational requirements, and data privacy concerns. Balancing safety with traffic efficiency and integrating new systems with existing infrastructure also present ongoing challenges [41]-[50].

2.3. Transportation Operations

AI applications in transportation operations include ramp metering, vehicle platooning, traffic flow prediction, signal timing optimization, and variable speed limits [51]-[53]. The backbone of these applications comprises advanced AI methods including computer vision, natural language processing (NLP), and machine learning [54]-[56]. AI applications offer significant benefits for transportation operations. For example, they could enhance traffic flow with up to 6% improvement reported in some projects [61], reduce congestion [62], and enhance energy efficiency [58]. AI-based systems optimize traffic signal timing [57]-[60], predict non-recurring traffic events, and enable proactive management strategies [65]-[67]. Innovations like truck platooning have shown potential fuel savings of up to 10% and reduced delivery costs by 30% [70]. As an example, the Florida Department of Transportation (FDOT) implemented AI-powered traffic management tools to optimize signal timing along urban arterials, aiming to reduce peak-hour congestion. However, implementing AI in transportation operations also faces challenges. These include the need for accurate real-time data collection [63], proper sensor placement [64], and multi-objective optimization in congested areas [69], [71]. Implementation requires specialized skills, highlighting the need for workforce development [72]. Costs vary widely, from $300,000 for research projects to $1 million for larger implementations [73]-[75], with significant portions allocated to software development and integration [76].

2.4. Autonomous Vehicles

Autonomous Vehicles (AVs) are revolutionizing transportation by integrating advanced AI methods with diverse data inputs [77], [78]. These inputs include cameras, LiDAR, naturalistic driving data, traffic signal data, social media feeds, and digital maps [79]-[81]. AVs process this information using computer vision, natural language processing, reinforcement learning, and deep learning [82], [83]. Key applications of AVs encompass perception and sensor fusion [84], prediction and planning [85], and human-machine interaction [86]. The potential benefits are significant, including improved safety, enhanced mobility, reduced congestion, and increased fuel efficiency [87], [88]. The Illinois Department of Transportation (IDOT) has launched the "Autonomous Illinois" initiative, establishing AV pilot zones through public-private-academic collaboration to support real-world autonomous vehicle testing. Challenges in AV technology include cybersecurity threats [89], job displacement concerns, and technical issues like performance in adverse weather [90], [91]. Legal and regulatory hurdles, particularly regarding data privacy and liability, also persist [92]-[100].

2.5. Digital Twins

Digital Twins (DTs) in transportation are virtual replicas of physical assets, systems, or processes that use real-time data to simulate, analyze, and optimize operations [77], [78]. They integrate various data inputs with AI methods (e.g., computer vision, natural language processing, reinforcement learning, deep learning, statistical learning, and machine learning algorithms) [79]-[82]. Key applications of DTs include safety analysis, urban planning, infrastructure management, transportation system simulation, vehicle and pedestrian tracking, and traffic management [83]-[85]. The benefits of DTs are significant. For example, DTs address the limitations of traditional surrogate safety measures by enabling high-fidelity, real-time replication of traffic environments, which allows for dynamic scenario testing, continuous safety evaluation, and proactive risk identification. This enhanced capability to simulate and analyze safety-critical events in a virtual setting holds the potential to significantly reduce crashes [86]. For bridge monitoring, DTs lead to cost savings by reducing unnecessary bridge replacements and increasing mobility [87]. In waterway systems, DTs contribute to improved operational efficiency and reduced transportation delays [88], [89]. DTs offer potential long-term savings through reduced site visits, improved maintenance procedures, and enhanced decision-making capabilities [90], [91]. A notable example includes the Washington State Department of Transportation (WSDOT), which partnered with the University of Washington to develop a digital twin of the I-90 floating bridge, achieving enhanced structural monitoring and an estimated return on investment of up to 2000%. However, implementing DT workflows faces challenges in procurement costs [92]. Moreover, the variability in material properties for infrastructure modeling, limitations in data availability, and bureaucratic delays in sensor installation are other obstacles to implementing DTs [93]-[96].

2.6. Generative AI

Generative AI creates content like text, images, and simulations based on user input, driven by advanced deep learning methods [101]-[103]. It has promising applications in transportation, particularly in autonomous driving, traffic prediction, etc. [104], [105]. In autonomous driving, Generative AI helps create realistic driving scenarios for training autonomous vehicles, improving their decision-making in complex, real-world situations [106]. Additionally, Generative AI enhances traffic simulations by modeling vehicle behavior and rare events, which are useful for urban planning and testing autonomous vehicles [107]. The California Department of Transportation (Caltrans) is piloting the use of Generative AI to support document summarization and internal report generation, streamlining workflows and enhancing knowledge management efficiency. However, implementing Generative AI in transportation comes with challenges. These include integrating diverse data sources, handling incomplete or sparse data, and ensuring real-time decision-making [108]. There are concerns about technology's vulnerability to adversarial attacks, which could affect safety [109]. Despite these challenges, Generative AI has the potential to transform the transportation industry by improving traffic management, simulation, and decision-making processes [110], [111].

The literature review above has identified six key domains, including Transportation Asset Management, Transportation Safety, Transportation Operations, Autonomous Vehicles, Digital Twins, and Generative AI, which are the focus areas for current and emerging AI applications in transportation and are the basis for the survey conducted in this report. By synthesizing recent research across these fields, the review provides a foundational understanding of the opportunities and challenges associated with AI adoption and exemplifies some of the specific AI in transportation projects in different state DOTs. These insights will directly inform subsequent project phases. In particular, the findings will guide the design of the stakeholder survey and follow-up interviews in further research tasks, ensuring that data collection efforts are grounded in evidence and aligned with practical implementation considerations. The literature review thus serves as a critical step in aligning academic research with real-world needs and shaping a data-driven roadmap for AI integration in transportation systems.

3. SURVEY DESIGN

To assess the current practices, benefits, and challenges associated with the adoption of AI in the transportation sector, a structured survey was developed and distributed among professionals across various transportation-related agencies. The survey has the following objectives:

- To understand the current state of AI applications in transportation practices.
- To evaluate practitioner perceptions of AI-related benefits and challenges.
- To identify gaps in data availability, technical expertise, infrastructure, and institutional capacity.
- To provide recommendations for facilitating the broader adoption of AI technologies for WisDOT.

The survey was designed to collect both quantitative and qualitative data from practitioners actively involved in AI-related projects or policy-making processes, enabling the research team to identify common application areas, data management practices, infrastructure needs, and perceived implementation barriers. The target population included public-sector transportation professionals, planners, engineers, IT specialists, and decision-makers across local, regional, and state agencies.

The survey comprised questions across three parts: (1) basic information, (2) AI application in transportation, and (3) cost and workforce development. It was designed with mixed-format questions that allowed for both quantitative analysis and qualitative insights, enabling respondents to provide detailed feedback on AI applications, organizational practices, and recommendations for WisDOT. More details about the questionnaire can be found in Appendix B. All survey data were stored securely in university-managed systems, and the project was conducted following IRB-exempt protocols for minimal-risk research.

This survey was jointly developed by the University of Wisconsin–Madison and the University of Wisconsin–Milwaukee, under the sponsorship of WisDOT, and was administered online via Qualtrics and disseminated through a combination of direct email invitations, professional network referrals, and targeted outreach through transportation and AI-related forums. The survey remained open for responses from February 11, 2025, with further follow-up interviews from March 31 to April 25. Participants were informed of the voluntary nature of the study, and no personally identifiable information was required unless they chose to provide contact information for follow-up. The survey collected responses from participants in 17 states, as shown in Figures 3.1 and 3.2. These responses provided a broad cross-section of perspectives and practices from a geographically and institutionally diverse sample.

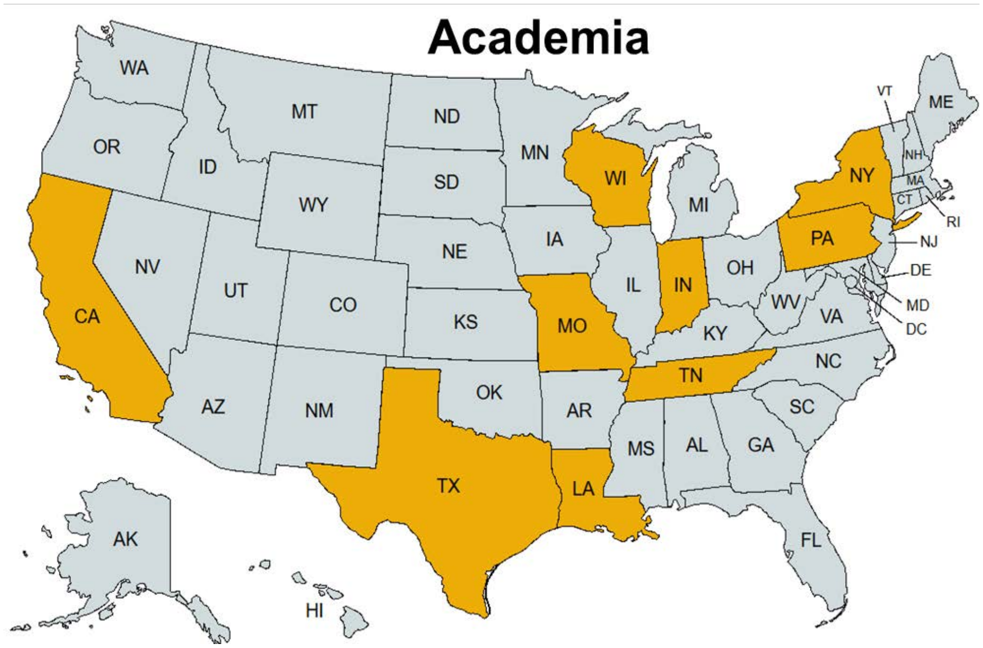

Figure 3.1 Location Distribution of Respondents by Academic Organizations

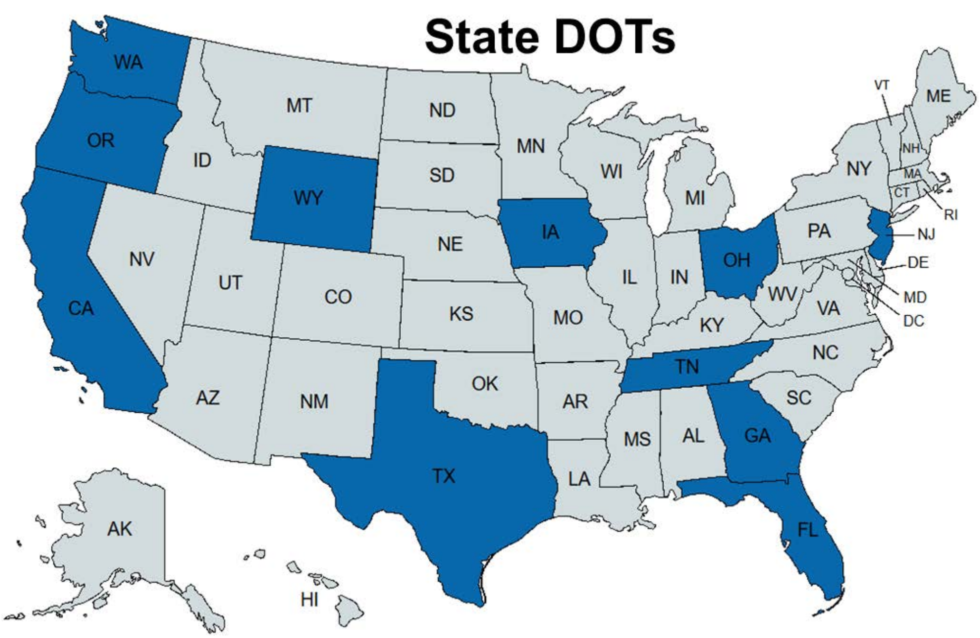

Figure 3.2 Location Distribution of Respondents by State DOTs

4. DATA ANALYSIS

4.1. Respondent Profile and AI Readiness

4.1.1 Survey Response Overview

The survey collected a total of 155 responses. Of these, 34 respondents completed the entire survey, 13 participants completed more than half of the survey questions, yielding sufficient data for analysis to support the key findings of this study. Figure 4.1 suggests that 75.0% of respondents identified as male, while 19.7% identified as female.

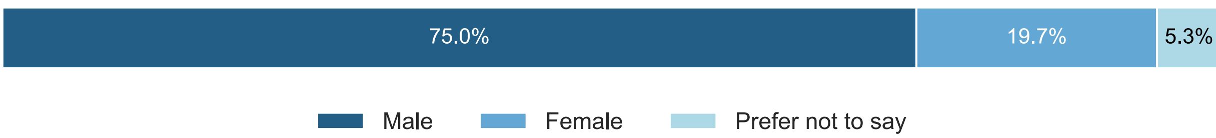

Figure 4.1 Gender Distribution of Survey Respondents

As shown in Figure 4.2, the 36-50 age group represents the largest segment at 42.1% of respondents. The second largest group is the 25-35 age bracket, accounting for 31.6% of participants. Older age groups make up smaller proportions of the sample, with respondents aged 51-60 representing 9.2% and those over 60 constituting 10.5%. The youngest demographic, respondents under 25, accounts for only 1.3% of the sample. This age distribution shows that most transportation professionals engaged with AI implementation are in their middle career stages (36-50 years), with significant representation from early-career professionals (25-35 years) as well.

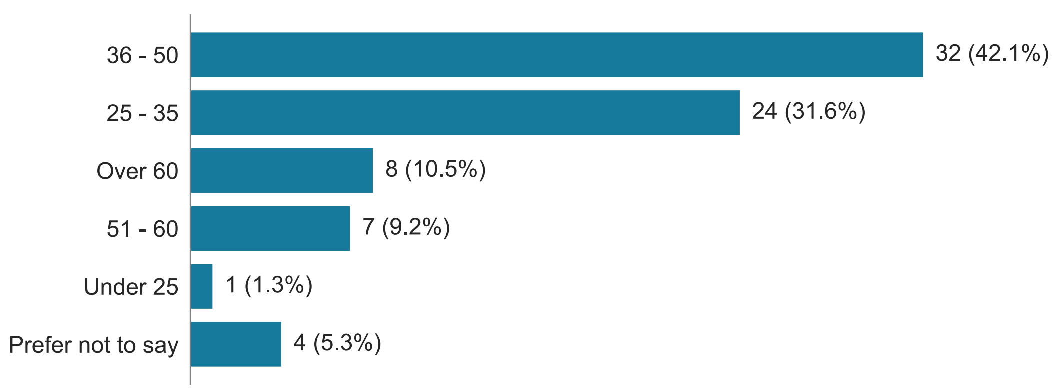

Figure 4.2 Age Distribution of Survey Respondents

For education levels, as shown in Figure 4.3, doctoral degree holders constituted the largest group at 47.4%, followed by those with bachelor's degrees and master's degrees. This educational distribution might suggest that professionals engaged with AI applications in transportation tend to possess advanced academic credentials, with nearly half holding doctoral degrees. The combined percentage of bachelor's and master's degree holders indicates that undergraduate and graduate education serve as a fundamental qualification for practitioners in this field.

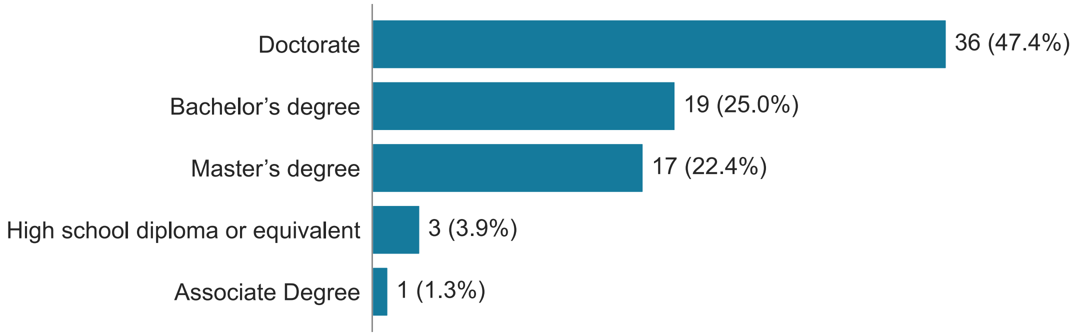

Figure 4.3 Educational Distribution of Survey Respondents

Regarding professional experience, Figure 4.4 illustrates the distribution of respondents' work experience. 51.3% of participants reported being in their current roles for less than 5 years, which suggests a relatively high proportion of professionals who have recently entered their positions. Longer-tenured professionals are less represented, with only 3.9% having worked in their current positions for 16-20 years and 5.3% for more than 20 years. This tenure distribution might reflect the relatively recent integration of AI technologies into transportation fields.

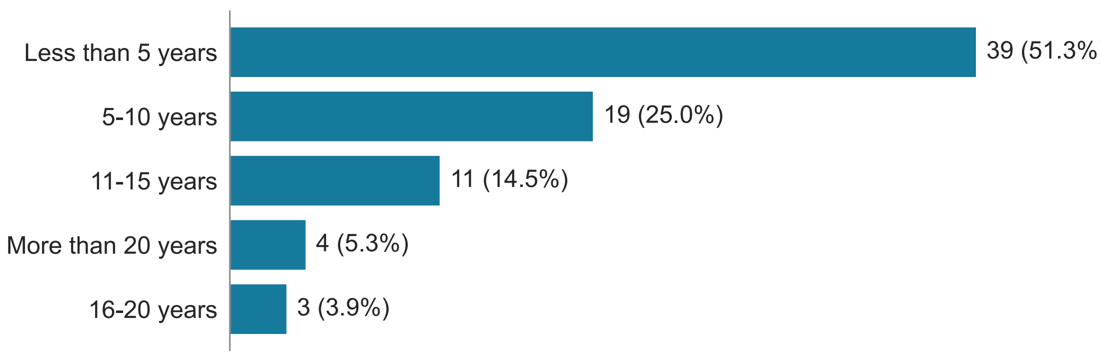

Figure 4.4 Professional Experience Distribution of Survey Respondents

Geographically, the respondents represent a diverse cross-section of transportation organizations across the United States. As shown in Figure 4.5, the Northeast region accounts for the largest proportion at 33.8%, followed by the South (28.6%), Midwest (20.8%), and West (16.9%). This geographic distribution provides a balanced perspective on AI implementation in transportation across different regional contexts, each with its own unique infrastructure challenges, regulatory environments, and technological adoption patterns.

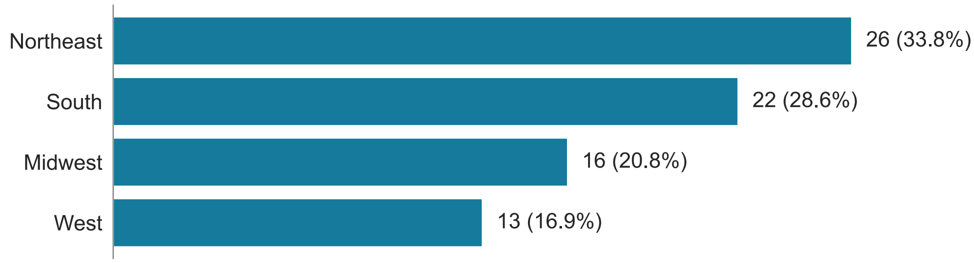

Figure 4.5 Regional Distribution of Survey Respondents

4.1.2 Professional Background of Respondents

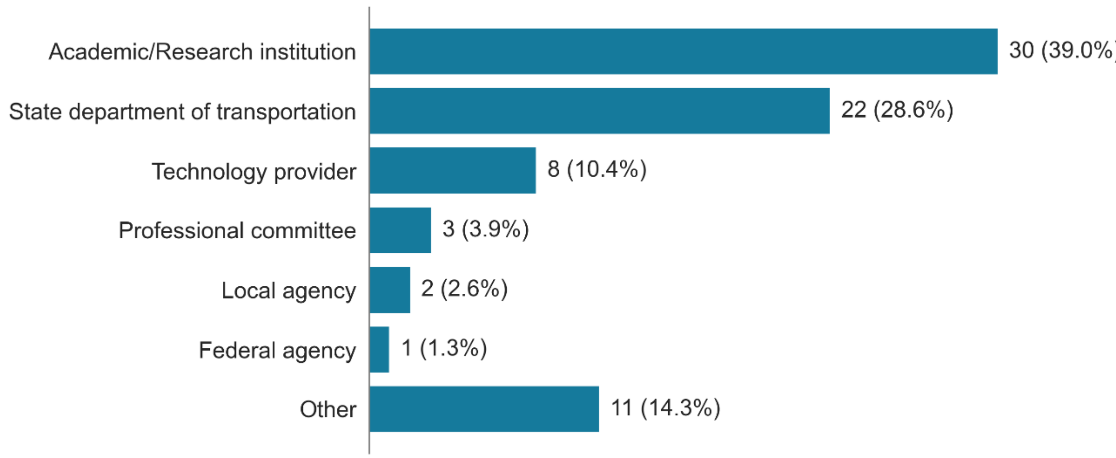

Figure 4.6 Distribution of Respondents across Organization Types

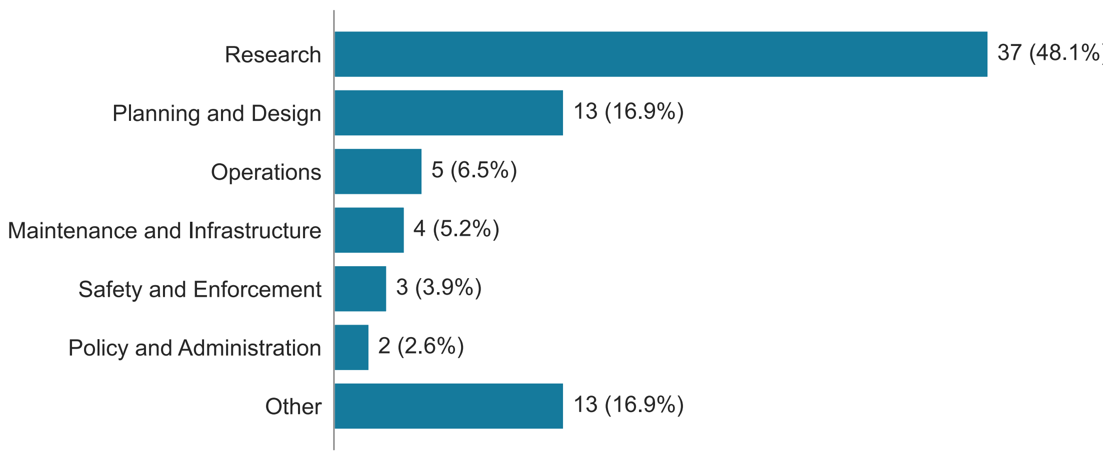

Figure 4.7 Distribution of Respondents across Different Functional Roles

As shown in Figure 4.6, most respondents were affiliated with academic or research institutions, followed by state departments of transportation. Other organizational types represented include technology providers, professional committees, local agencies, and federal agencies. Figure 4.7 illustrates the distribution of respondents across different functional roles within the transportation sector. “Research” emerges as the predominant functional area, accounting for nearly half of all respondents. “Planning and Design” functions represent the second largest category at 16.9%. Operations (6.5%), “Maintenance and Infrastructure” (5.2%), Safety and Enforcement” (3.9%), and “Policy and Administration” (2.6%) comprise the remaining functional categories.

4.1.3 AI Experience Levels

According to the survey responses, 86.8% of respondents reported having been involved with AI-related applications in their professional capacity. Among those with AI experience, the distribution of experience duration is particularly revealing (Figure 4.8). 70.8% reported having less than five years of experience working with AI technologies. 26.2% of respondents indicated medium-term experience ranging from five to 15 years, while only a small fraction (3.1%) reported extensive experience exceeding 15 years.

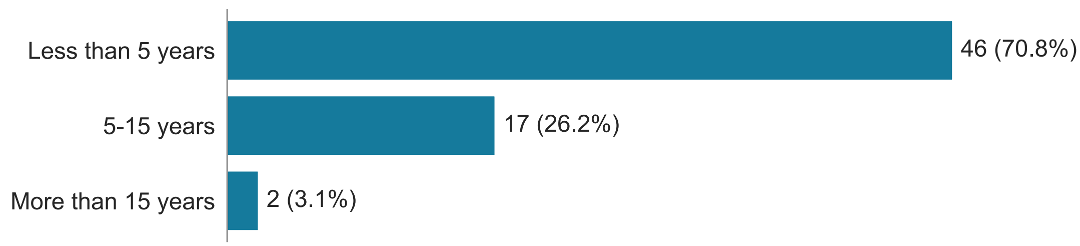

Figure 4.8 AI Experience Distribution of Respondents

This pattern strongly suggests that AI adoption in the transportation sector is a relatively recent phenomenon. The concentration of professionals with less than five years of experience aligns with the broader timeline of AI advancement and application in transportation contexts, which has accelerated significantly in recent years.

4.1.4 AI Training and Professional Development

The survey results reveal significant gaps in AI-related training and professional development across the transportation sector. As illustrated in Figure 4.9, nearly half of all respondents (48.3%) reported receiving no formal AI-related training whatsoever. Among those who had received some form of AI training, the distribution across different training categories is notably uneven. Approximately one-third of respondents reported receiving training focused on AI introduction and relevant theories, indicating a basic level of conceptual familiarity. However, only 17.2% of respondents reported receiving training in each of three critical categories: AI tools and platforms, data ethics and security, and other specialized AI domains.

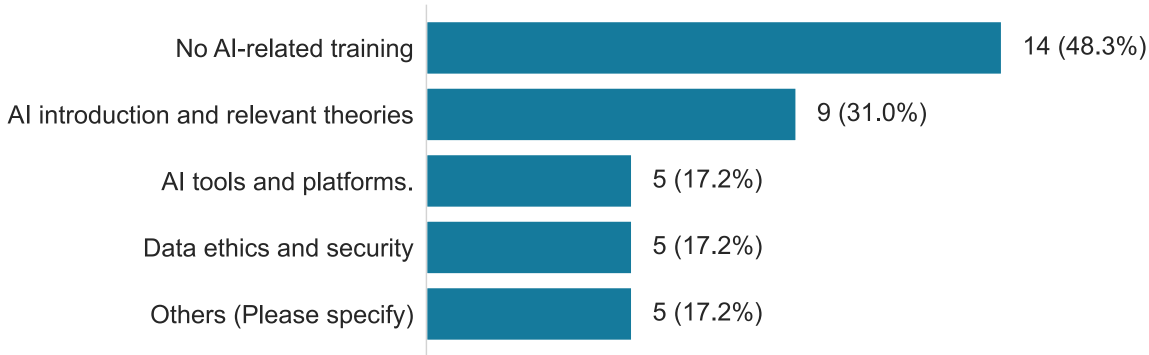

Figure 4.9 AI-related Training and Professional Development across Transportation Sectors

This distribution highlights a concerning imbalance between theoretical knowledge and practical implementation skills. While a moderate proportion of transportation professionals have been exposed to foundational AI concepts, far fewer have received the specialized technical and essential ethical training for effective implementation. The limited training in AI tools and platforms is also noteworthy, as it may constrain organizations' ability to operationalize AI solutions even when conceptual understanding exists. Lastly, there is a significant gap in ethics and security training that warrants special attention, given the increasing concerns about privacy, bias, and security vulnerabilities in AI systems. As transportation agencies deploy increasingly sophisticated AI applications that interact with the public and critical infrastructure, ensuring ethical implementation becomes paramount. These findings strongly suggest the need for more comprehensive, structured AI training programs within transportation organizations. Effective professional development strategies should balance theoretical foundations with practical implementation skills and ethical considerations, creating a workforce equipped to harness AI's potential while mitigating associated risks.

4.1.5 Perceived Effectiveness of AI Training

Beyond the availability of AI training programs, the survey also explored perceptions of training effectiveness among those respondents who indicated they had received such training. The results, depicted in Figure 4.10, reveal a clear trend toward moderate satisfaction rather than strong endorsement. Among respondents who had received AI training, the largest group (34.5%) rated their experience as moderately effective (3 on a 5-point scale). However, a substantial share expressed concerns, with 31.0% rating their training as somewhat ineffective (2) and 17.2% as entirely ineffective (1). In contrast, relatively few participants rated their training as highly effective: only 10.3% gave a score of 5, and 6.9% rated it as 4.

These results suggest that among those who have received AI training, many found the programs only moderately effective, with nearly half reporting negative experiences. Although a small portion expressed high satisfaction, the overall distribution points to substantial room for improvement in current efforts.

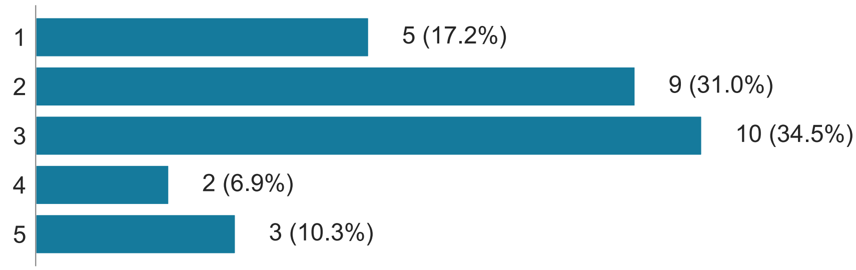

Figure 4.10 Rating Distribution of Effectiveness of AI Training

4.1.6 AI Skills Gap Analysis

To better understand the specific areas where transportation professionals feel underprepared for AI implementation, the survey asked respondents to identify gaps between their current AI skills and those needed for effective application. The results, shown in Figure 4.11, reveal perceived skill deficiencies.

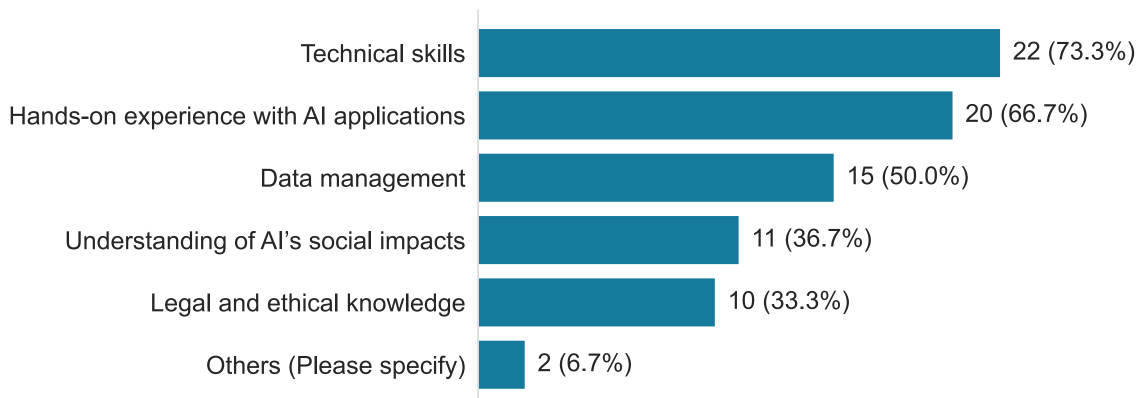

Figure 4.11 Selection Distribution of Gap between Current and Needed Skills for AI Applications

Technical skills emerged as the most widely acknowledged gap, with 73.3% of respondents identifying this as an area of deficiency. This finding aligns with the previously observed limited availability of training in AI tools and platforms, suggesting a significant mismatch between the technical competencies required for AI implementation and the current workforce capabilities. Closely related, hands-on experience with AI applications was identified as the second most prevalent gap. This finding is particularly noteworthy given the earlier observation that 70.8% of respondents have less than five years of AI experience, reinforcing the conclusion that many transportation professionals are still in the early stages of practical AI implementation.

Data management skills represented another significant area of concern, with half of all respondents identifying this as a skills gap. This finding is especially relevant given the data-intensive nature of AI applications in transportation, where effective collection, cleaning, integration, and governance of diverse data sources is often a prerequisite for successful implementation. By contrast, respondents were somewhat less likely to identify gaps in their understanding of AI's broader implications. Just 36.7% noted deficiencies in understanding AI's social impacts, while a similar proportion (33.3%) identified gaps in legal and ethical knowledge. This distribution of responses reveals a critical insight: the most pressing skill gaps in the transportation sector relate to practical implementation rather than conceptual understanding.

These findings strongly suggest that workforce development initiatives should prioritize practical, hands-on training focused on technical skills and real-world applications, complemented by foundational data management competencies. Bridging these skills gaps will be essential for transportation agencies seeking to realize the full potential of AI technologies in addressing sector challenges.

4.1.7 Recommendations for AI Readiness

The survey also solicited respondents' recommendations for specific actions that transportation agencies, particularly WisDOT, should take to enhance their AI readiness. The results, depicted in Figure 4.12, demonstrate a strong consensus around several key priority areas.

Providing AI-focused training programs emerged as the most widely endorsed recommendation, with 77.8% identifying this as a priority action. This finding directly addresses the previously identified gaps in both training availability and effectiveness. Two strategic priorities received equal endorsement from respondents (66.7% each): developing AI-specific policies and establishing robust data management systems. The strong support for policy development reflects recognition that effective AI implementation requires clear governance frameworks addressing procurement, deployment, maintenance, and evaluation of AI solutions. Similarly, the emphasis on data management systems acknowledges that high-quality, well-organized data is the foundation upon which successful AI applications are built.

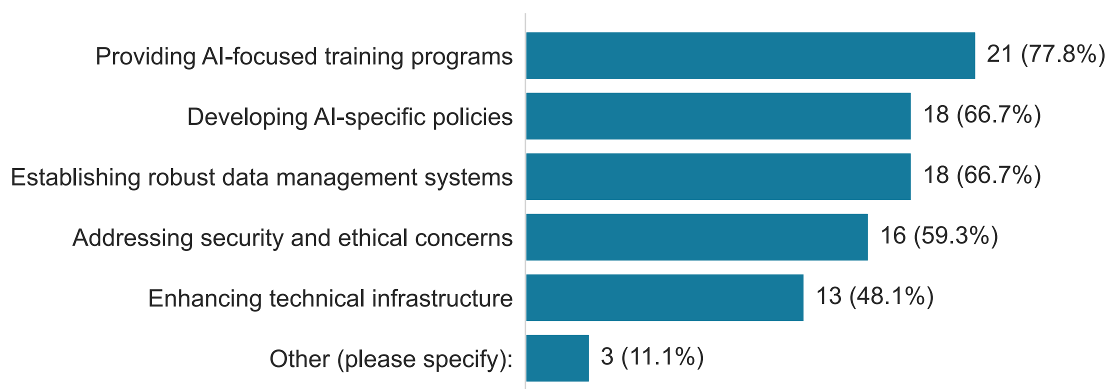

Figure 4.12 Distribution of AI-related Training Programs

Addressing security and ethical concerns ranked as the fourth most endorsed recommendation. This level of support indicates growing awareness of the potential risks associated with AI deployment in transportation contexts, where applications may impact public safety, privacy, and equitable service delivery. Enhancing technical infrastructure received support from 48.1% of respondents.

Collectively, these recommendations reveal a strong consensus on the foundational elements required for transportation agencies to advance their AI readiness. Rather than focusing narrowly on specific AI applications or technologies, respondents emphasized the importance of building organizational capacity through training, governance frameworks, and data systems. This suggests that transportation professionals recognize AI readiness as a multifaceted challenge requiring coordinated efforts across technical, organizational, and policy dimensions.

4.2. Survey Topic

This subsection presents additional analyses on selected topics that synthesize responses across multiple survey questions. These analyses aim to uncover deeper patterns and relationships that may not be evident from individual question results.

4.2.1 Quality and Challenge of Different Data Types

This topic investigates the perceived data quality and preparation difficulty of four common data types used in AI-based transportation applications. The four common data types include 1) vision data, 2) text data, 3) map data, and 4) traffic data. For data preparation difficulties, we evaluate four dimensions, which are data collection, data cleaning, data labeling, and data management.

(1) Findings from Survey Results

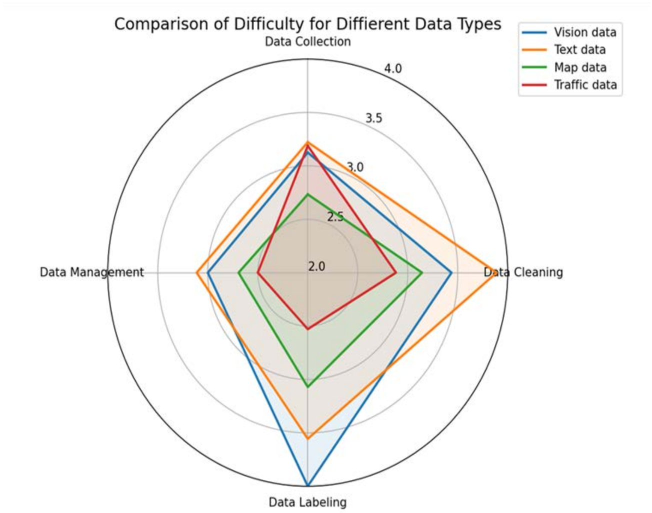

Figure 4.13 Comparison of Difficulty for Different Data Types

As shown in Figure 4.13, survey results indicate that map data and traffic data are considered high-quality and low-difficulty sources. Their structured nature and integration within existing GIS and ITS systems make them the most reliable and cost-effective for AI applications. These data types are readily available through traffic sensors, historical datasets, and mapping services, contributing to their consistent usability.

In contrast, text data, especially that originating from social media or incident narratives--was rated as having the lowest overall quality due to its inherent noise, informal language, and unstructured format. Among the four difficulty dimensions, data cleaning was considered the most challenging aspect for text data. The presence of misspellings, abbreviations, sarcasm, and contextually ambiguous expressions makes it particularly difficult to process. As a result, preparing text data requires advanced NLP techniques, domain-specific filters, and often manual verification to extract reliable features.

Vision data, on the other hand, is recognized for its high potential value in transportation applications such as object detection, traffic incident recognition, and behavior prediction. However, it poses significant challenges in terms of data labeling. Annotating vision data demands fine-grained, often frame-by-frame labeling, which is time-consuming and requires significant domain expertise--especially when dealing with complex traffic scenes or safety-critical events. While data collection (via traffic cameras or drones) and cleaning are generally manageable, managing large video files and ensuring annotation consistency across datasets introduce additional burdens.

In summary, Map and Traffic data are seen as low-effort, high-value inputs, whereas text and vision data, though powerful, require significant preparation efforts. These insights underscore the importance of targeted investments in data readiness for successful AI deployment.

(2) Discussions on Future Development

Based on the findings above, we provide the following strategic recommendations to assist WisDOT in enhancing data management and development:

- Enhance data cleaning through NLP tooling: Develop transportation-specific NLP pipelines to clean and structure incident reports, traveler feedback, and social media text. Collaborate with academic institutions and private vendors to co-develop pretrained language models for transportation context.
- Promote fusion of high-quality map and traffic data: Integrate map and real-time traffic data into predictive AI models for applications such as incident forecasting, congestion management, and dynamic routing. Couple these with existing ITS infrastructure to improve real-time operational decision-making.

- Address rural data equity and infrastructure gaps: Expand data acquisition infrastructure in rural and underserved regions to balance spatial data availability and avoid urban-only AI deployment bias. Utilize mobile sensing platforms or drones to extend coverage and feed real-time data from sparsely monitored areas.

4.2.2 Work Experience and Satisfaction with AI

(1) Findings from Survey Results

This section explores the relationship between years of AI-related work experience and satisfaction with performance across six AI application areas in the transportation domains, which are Asset Management, Transportation Safety, Traffic Operations, Digital Twins, Autonomous Vehicles, and Generative AI. As employees gain experience, they may have different perspectives on the same things, which can help DOT implement targeted measures for employees with different ranges of work years.

As illustrated in Figure 4.14, there is a significant correlation between work experience and satisfaction levels. Respondents with more than 10 years of experience (11-15 years and >15 years group) reported notably higher satisfaction with traditional and well-established AI applications, particularly in Asset Management. Specifically, satisfaction scores in this category increased from 1.08 (for <5 years group) to 4.00 (for >15 years group), suggesting that seasoned employees may better recognize the tangible benefits of AI in infrastructure lifecycle planning and resource optimization.

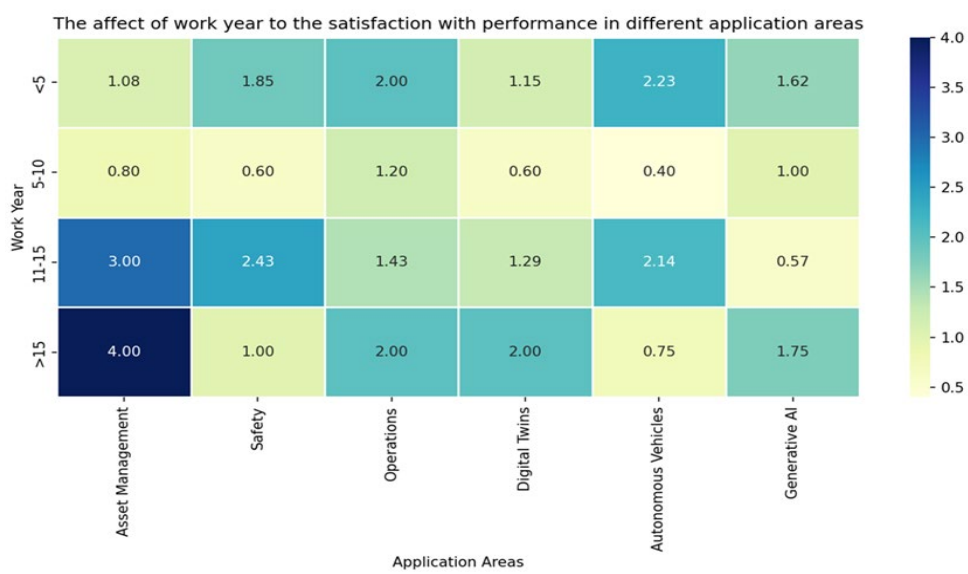

Figure 4.14 Effect of Work Year on Satisfaction in Different Application Areas

In contrast, less experienced employees (<5 years group) exhibited more evenly distributed satisfaction across all application areas, including emerging technologies such as Generative AI and Autonomous

Vehicles. This suggests a greater openness and optimism toward novel or experimental AI domains among early-career respondents, possibly due to their academic exposure or technological fluency.

Interestingly, the 5-10 years group reported overall lower satisfaction scores across nearly all domains, with minimal variation between applications. This dip may reflect transitional career stages where expectations are high, yet direct control over AI implementation or evaluation remains limited. For instance, this group rated Transportation Safety and Autonomous Vehicles particularly low (0.60 and 0.40), potentially indicating a mismatch between expectations and observed system maturity.

(2) Discussions on Future Development

The findings highlight that employee satisfaction with AI applications in transportation varies significantly by work experience, which offers important guidance for designing differentiated collaboration strategies. We encourage WisDOT to adopt the following targeted approaches:

- Task assignment based on experience strengths: (a) Assign highly experienced employees (>10 years) to lead deployment and quality assurance in mature AI domains such as Asset Management and Traffic Operations. (b) Involve the 5-10 years cohort in cross-domain coordination roles, bridging technical implementation with operational needs, while gradually building their applied experience and confidence. (c) Engage early-career employees (<5 years) in pilot projects and experimental applications like Generative AI and digital twins, where innovation, adaptability, and fresh technical perspectives can accelerate development.
- Differentiated AI application training for different levels of employees: (a) For senior employees: emphasize strategic oversight, ethical governance, and risk-informed decision-making in AI system deployment. (b) For mid-career employees: focus on hands-on modeling, interfacing with AI tools, and project implementation case studies. (c) For junior employees: provide foundational AI literacy, data pipeline skills, and application-specific toolkits to enable rapid engagement.
- Cultivate inclusive AI development culture: Foster an internal culture that values diverse experience perspectives in AI decision-making. Encourage inclusive feedback loops, ensuring that insights from each career stage help shape workflow design and user satisfaction metrics.

4.2.3 AI Experience Gap and Satisfaction

(1) Findings from Survey Results

This topic examines how employees with different balances between work year and AI work experience evaluate satisfaction with AI applications across six transportation domains: Asset Management, Transportation Safety, Traffic Operations, Digital Twins, Autonomous Vehicles, and Generative AI.

Respondents were divided into two groups, Group 1 includes employees whose work experience significantly exceeds their AI usage experience (a gap of more than five years), representing a cohort with domain knowledge but limited exposure to AI tools. Group 2 includes Employees whose work experience closely matches their AI usage experience, typically more integrated into AI-enhanced workflows.

The difference in satisfaction levels between the two groups can be a good indicator of how employees perceive the application of AI in different areas, including reliability and applicability.

As illustrated in Figure 4.15, clear satisfaction differences emerge between these two groups across the application areas. In Asset Management and Transportation Safety, satisfaction levels between the two groups are nearly equivalent, suggesting that these fields benefit from more mature, well-integrated AI tools. Group 1 employees --despite limited AI familiarity--likely perceive these tools as credible due to their widespread institutional adoption and alignment with established workflows.

However, substantial gaps appear in the remaining four areas. Specifically, in Traffic Operations and Generative AI, Group 2 reports significantly higher satisfaction, while Group 1 shows clear skepticism or disengagement. In Digital Twins and Autonomous Vehicles, the gap persists, albeit to a lesser extent.

These results suggest that Group 1 may experience a “trust gap” regarding newer or less mature AI technologies. Their reliance on traditional engineering and planning methods may lead to greater caution or lower perceived utility when encountering emerging AI-driven approaches. Conversely, Group 2 employees, often more digitally native or technologically fluent, display greater comfort with AI integration and more positive attitudes toward its evolving capabilities.

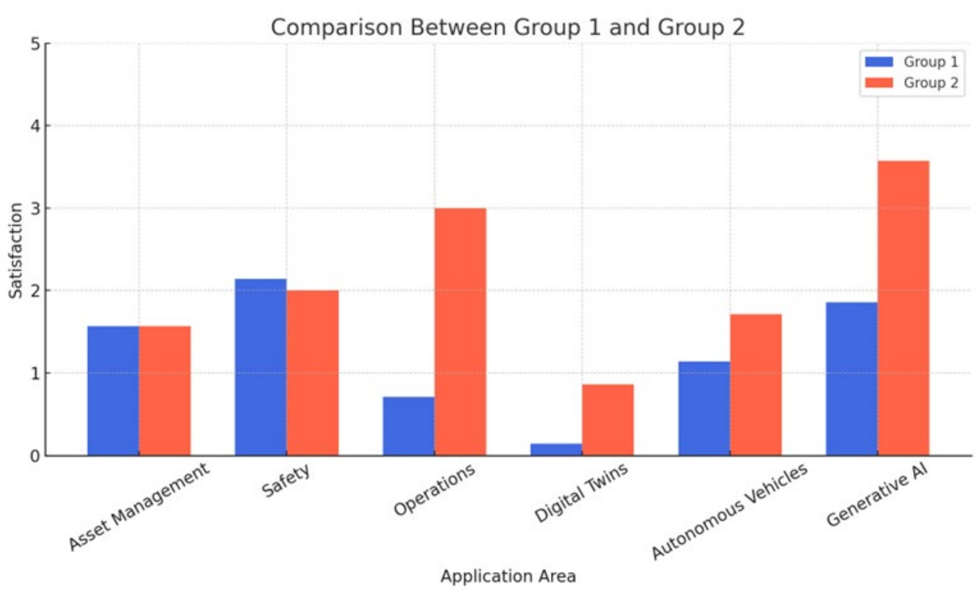

Figure 4.15 Comparison Between Employees with Different Work Years and AI Work Experience

(2) Discussions for Future Development

To ensure equitable and effective adoption of AI technologies across the workforce, the following recommendations are proposed for WisDOT:

- Bridge the trust gap through use-case exposure: Organize field demonstrations and data-driven case studies that showcase the performance of AI in operations, digital twins, autonomous vehicles, and generative AI. Highlight practical outcomes and real-world benefits to help experienced professionals see the tangible value of emerging AI applications.
- Develop dual-track learning paths: For Group 1, focus training on AI interpretation, validation techniques, and hybrid approaches that blend traditional methods with AI support. For Group 2, offer advanced AI development training and opportunities to lead pilot programs in novel fields such as generative design and simulation-based control. This means that grouping employees based on AI experience is effective, which will make further AI training more valuable.
- Adapt AI system interfaces to user familiarity: Tailor the usability and transparency of AI systems to support diverse user profiles. For example, provide explainable AI features and simplified dashboards for experienced engineers less accustomed to AI models.

4.2.4 Potential Benefit and Expected Timeframe of Different AI Applications

(1) Findings from Survey Results

This section evaluates how respondents perceive the potential benefit and expected timeframe across six key AI application areas in transportation domains, including Asset Management, Transportation Safety, Traffic Operations, Digital Twins, Autonomous Vehicles, and Generative AI. Potential benefits are measured through a five-point scale, with higher scores representing more substantial returns. The expected timeframe is divided into short, medium, and long term, representing 1-3 years, 4-7 years, and 8+ years, respectively. Areas where potential benefits and expected timeframe match should be the focus of WisDOT development, while for areas where the two metrics are out of balance, attempts need to be made to explore new research approaches. These findings will be particularly critical in resource allocation and roadmap.

As shown in Figure 4.16, the average potential benefit remains consistently high across all domains (ranging from 3.9 to 4.3), indicating general optimism about the transformative potential of AI in transportation. However, the expected timeframe for realizing these benefits varies significantly by application, revealing important insights into development feasibility, adoption readiness, and return on investment cycles.

Notably, Autonomous Vehicles domain exhibits a disproportionately long expected timeframe despite a moderate benefit rating (with an average of 3.95). This mismatch suggests respondents perceive AV-related

AI as promising but not yet practical, likely due to high R&D costs, regulatory hurdles, and deployment complexity. In contrast, domains such as Asset Management and Transportation Safety receive high benefit ratings (with an average larger than 4.1) and short-to-medium expected timeframes, reflecting greater maturity of existing AI solutions, better integration with current workflows, and faster realizable value.

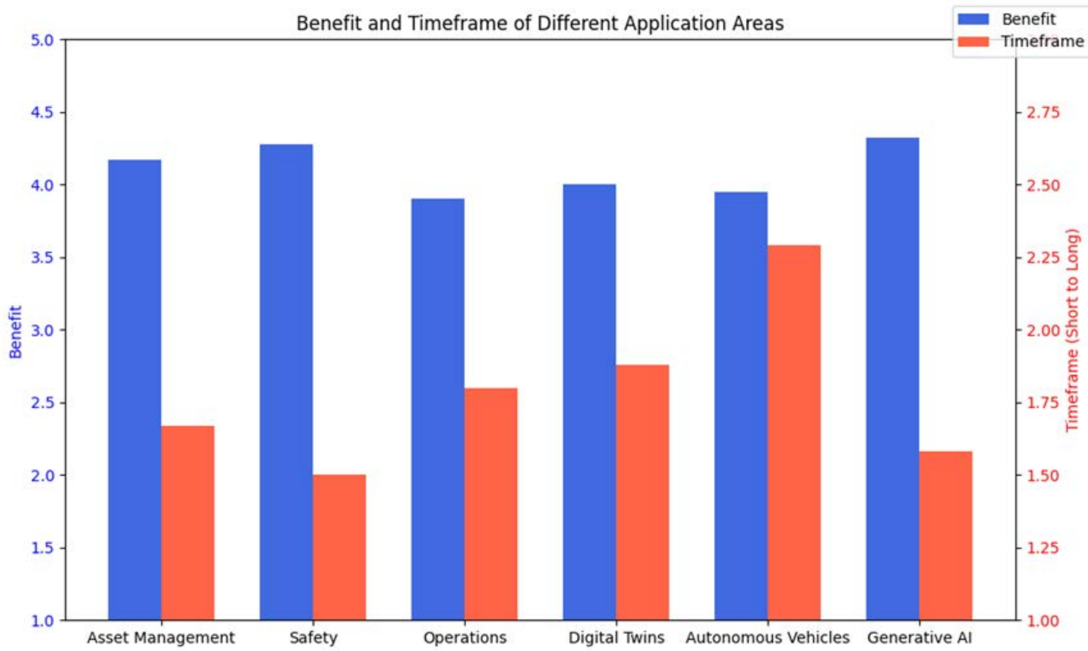

Figure 4.16 Potential Benefits and Expected Timeframe of Different AI Application Areas

Traffic Operations, Digital Twins, and Generative AI fall in the mid-spectrum. Although Generative AI shows relatively high perceived benefit, it is also associated with a shorter timeframe, suggesting that the industry sees this as an emerging but rapidly deployable technology, likely due to the increasing availability of user-friendly tools and cloud-based platforms.

(2) Discussions on Future Development

To strategically prioritize AI deployment across functional areas, WisDOT should consider the following insights and actions:

- Adopt a dual-lens evaluation framework: Impact vs. Readiness: Use a benefit-timeframe matrix to categorize AI applications by strategic fit: Promising investments: High benefit, short or medium timeframe, training and development programs should be in place (e.g., asset management, generative AI). Long-horizon innovation: Moderate benefit, long timeframe, consider changing research methodology or requesting resources from research institutions (e.g., autonomous vehicles).

- Accelerate implementation in high-return, near-term areas: Prioritize funding and talent for AI-enabled asset management and safety systems, where tools are proven and benefits can be captured early. Scale deployment through integration with existing ITS and infrastructure management projects.
- De-risk long-term AI investment through phased pilots: For Autonomous Vehicle technologies, adopt a modular, phased approach focusing first on traffic simulations that have a small cost and risk factor, along with small, controlled environment experiments to demonstrate value over time. Collaborate with research institutions and OEMs to share costs and reduce uncertainty.

4.2.5 Benefits and Risks of AI in Different Application Domains

To evaluate the perceived benefits and risks associated with various AI application areas in transportation, we utilized two metrics: the Potential Benefit Score and the Potential Risk Score. Both scores range from 1 to 5, with higher values indicating greater perceived benefits or risks, respectively. Furthermore, to visualize the tradeoff between benefits and risks, we employed a bubble chart representation, where each point corresponds to a specific combination of benefit and risk scores, and the size of each bubble reflects the number of responses. This approach enables a nuanced interpretation of how benefits and risks are jointly perceived within each AI domain, supporting more informed discussions and strategic planning.

(1) Transportation Asset Management

Transportation asset management is considered one of the most promising areas for AI integration. The results of this analysis support that perception, as illustrated in Figure 4.17.

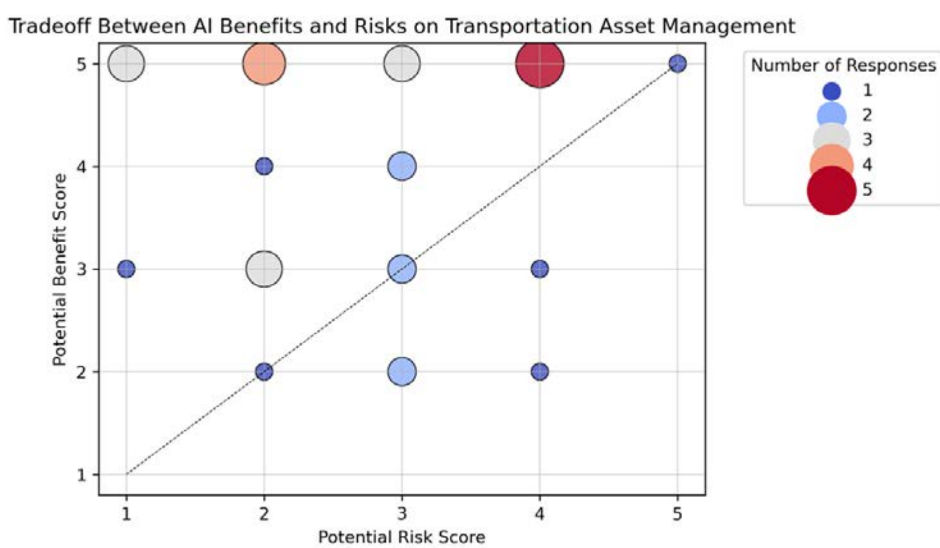

Figure 4.17 Benefits and Risks Analysis on Transportation Asset Management

Most respondents assigned very high benefit scores to AI in asset management, indicating strong confidence in its potential to optimize maintenance scheduling and predict infrastructure failures. The dominance of high-benefit responses, especially in conjunction with larger bubble sizes (five respondents rated benefit=5 and risk=4), demonstrates a consolidated belief in the practical value and scalability of AI in this mature and data-rich field. However, despite optimism, the risk scores are non-negligible. A significant portion of respondents placed AI in asset management within the high-risk zone (risk>3). This likely reflects concerns over system reliability, data integration challenges, lack of interpretability in predictive models, and the need for human oversight in infrastructure-related decisions.

(2) Transportation Safety

Transportation safety is widely recognized by researchers and practitioners as a high-priority domain for the integration of AI technologies, given its direct impact on public well-being and policy initiatives. The analysis results, as shown in Figure 4.18, further reinforce this perception. The analysis results reveal dense clustering around (benefit=5, risk=3), (benefit=4, risk=3), and (benefit=4, risk=2), suggesting that most respondents strongly believe in the substantial benefits AI can deliver in enhancing transportation safety. These benefits may include improved incident detection, predictive crash modeling, real-time hazard warnings, and enhanced situational awareness for operators.

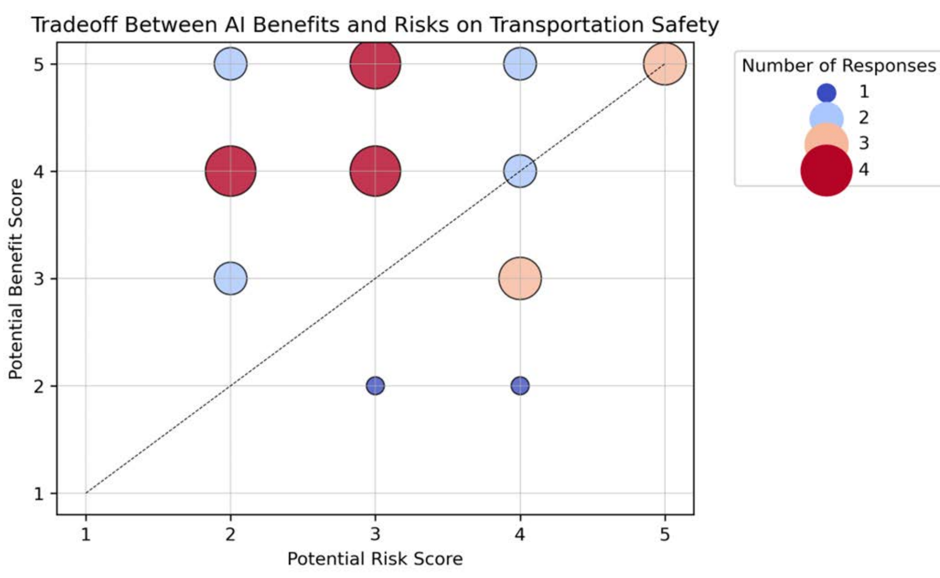

Figure 4.18 Benefits and Risks Analysis on Transportation Safety

Importantly, most points lie well above the diagonal line, which indicates that perceived benefits consistently outweigh perceived risks for AI applications in this domain. Compared to other areas, transportation safety emerges as one of the most trusted fields for AI deployment, reflecting growing reliability in mature technologies. Nevertheless, a moderate level of perceived risk remains below the diagonal line, likely linked to concerns about data privacy challenges and model transparency. However, the relatively lower positioning of risk compared to benefit suggests that such concerns are not seen as insurmountable barriers.

(3) Traffic Operations

Transportation operations, encompassing traffic control, congestion management, and incident response, represent a critical application area for AI integration. The results presented in Figure 4.19 highlight a generally optimistic view about the role of AI in this domain.

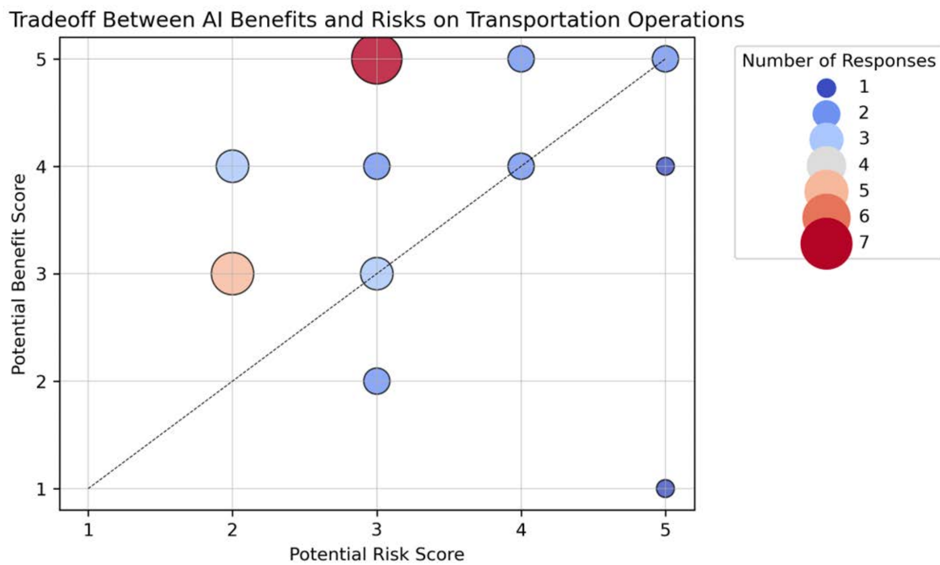

Figure 4.19 Benefits and Risks Analysis on Transportation Operations

The analysis results show a strong concentration at the (benefit=5, risk=3) position, with many other responses located above or near the diagonal line. This pattern indicates that respondents widely perceive AI as delivering high benefits for transportation operations, particularly in enhancing efficiency, real-time responsiveness, and system reliability. The dense clustering around the highest benefit scores suggests a strong stakeholder confidence that AI technologies, such as predictive traffic modeling and adaptive signal control, can significantly improve operational performance.

While the perceived risk is moderate (centered around risk=3), it is generally viewed as manageable relative to the expected benefits. Risks may relate to system integration complexity, data quality issues, and cybersecurity vulnerabilities. However, the fact that most points stay near or above the benefit-risk diagonal line indicates that these concerns do not outweigh the perceived advantages.

(4) Digital Twins

Digital Twins, which create dynamic virtual models of physical transportation systems, have attracted growing attention as a transformative application of AI. The analysis results, as shown in Figure 4.20, reveal a generally favorable perception of AI's role in this domain. The analysis results show that most responses stay above the diagonal line, with concentrations at (benefit=5, risk=3) and (benefit=4, risk=3). This distribution indicates that respondents see Digital Twins as offering high benefits with manageable levels of risk. Key perceived benefits likely include enhanced infrastructure monitoring, predictive maintenance, scenario simulation for traffic planning, and real-time system optimization.

The consistent clustering above the diagonal suggests that respondents hold a positive outlook toward Digital Twin applications. They recognize the power of AI-enhanced simulation and prediction tools to improve decision-making and resource allocation without perceiving excessive risk. Identified risks, below the diagonal line, may stem from model fidelity issues, data integration complexity, and the challenges of keeping virtual representations synchronized with real-world conditions.

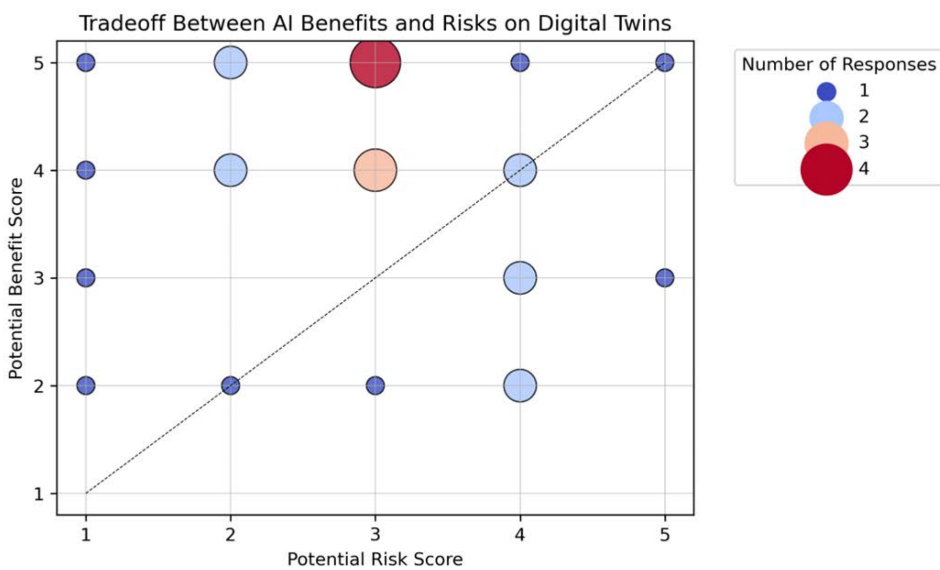

Figure 4.20 Benefits and Risks Analysis on Digital Twins

(5) Autonomous Vehicles

Autonomous Vehicles (AVs) represent one of the most high-profile and transformative areas for AI applications in transportation. However, their development has also brought with it enormous complexity and uncertainty, particularly regarding safety, regulation, and public trust. The survey results in Figure 4.21 reflect this duality, but also reveal a notable distinction compared to other application areas.

Specifically, the analysis shows a dense concentration of responses at the (benefit=5, risk=5) coordinate, underscoring respondents' recognition of both the extraordinary potential and the significant risks of AV technologies. Anticipated benefits include enhanced traffic safety, reduced congestion, improved mobility access, and increased operational efficiency. However, these are tempered by concerns over system reliability, cybersecurity threats, legal liabilities, and challenges with public acceptance.

Unlike other domains where perceived benefits tend to outweigh or at least balance perceived risks, AV-related responses more frequently fall below the diagonal, suggesting that many respondents see risk exceeding benefit. This trend reflects a more cautious and measured outlook: while stakeholders acknowledge the long-term promise of AVs, they also express heightened concern about unresolved barriers that could delay or even compromise their deployment. The distribution highlights that realizing the transformative potential of AVs will demand sustained technological innovation, robust policy frameworks, and proactive stakeholder engagement.

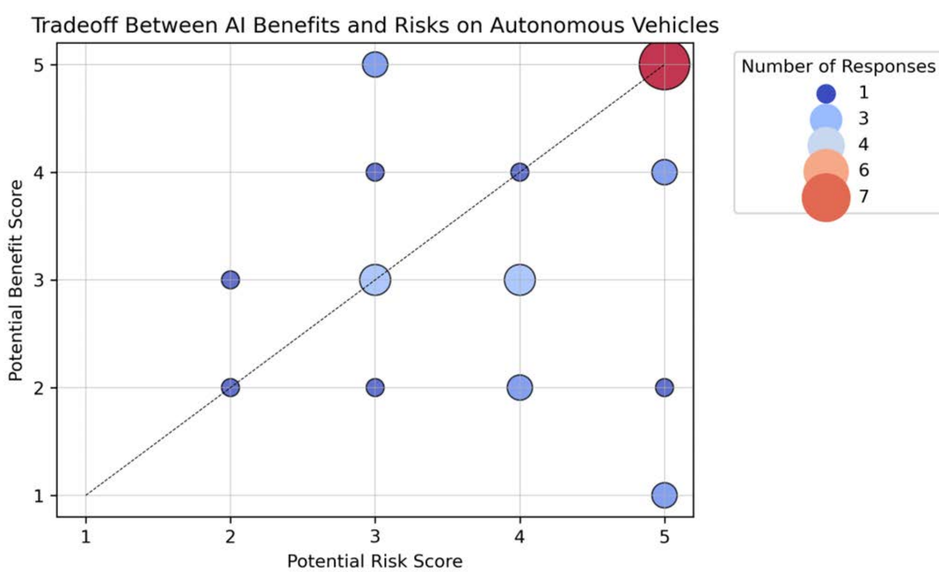

Figure 4.21 Benefits and Risks Analysis on Autonomous Vehicles

(6) Generative AI

Generative AI, including technologies such as large language models (LLMs) and generative design tools, has recently gained traction in transportation research and operations. However, perceptions of its maturity and risk profile remain mixed. The analysis results in Figure 4.22 highlights these nuances.

The analysis results indicate that responses are clustered around high benefit scores (particularly 5), coupled with moderate-to-high risk scores (ranging from 2 to 4). While most respondents acknowledge the strong potential of generative AI for accelerating documentation, scenario generation, and design automation, there is greater dispersion in risk perception compared to more established domains like Transportation Asset Management or Safety.

This dispersion suggests that respondents view generative AI as promising but still relatively immature, with concerns tied to model reliability, explainability, data bias, and the risk of producing inaccurate or inappropriate outputs. Respondents who gave lower risk scores were likely to be optimistic about current advancements in model fine-tuning and governance frameworks. Other respondents who gave higher risk scores emphasized caution, particularly in safety-critical or policy-sensitive contexts.

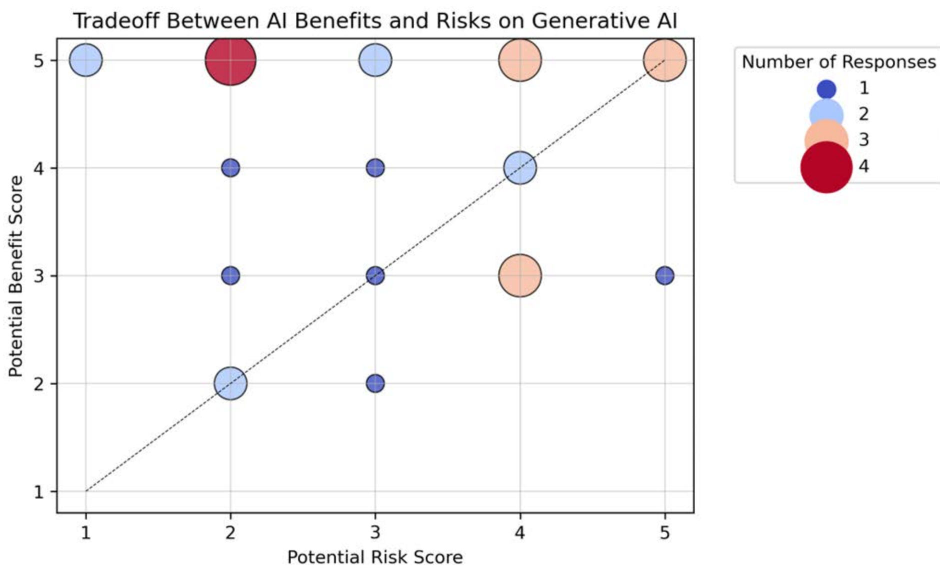

Figure 4.22 Benefits and Risks Analysis on Generative AI

(7) Tradeoff Between AI Benefits and Risks

The average potential benefit scores and potential risk scores for each AI application domain are summarized in Table 4.1 and analyzed as a whole. In this subsection, they will be analyzed to explore the tradeoff between AI benefits and risks.

Table 4.1 Summary about Benefits and Risks for Each Application

Applications	Potential Benefit Score	Potential Risk Score
Transportation Asset Management	4.17	2.84
Transportation safety	4.28	3.37
Transportation Operations	3.91	3.33
Digital Twins	4.03	2.76
Autonomous Vehicles	3.95	4.15
Generative AI	4.32	3.11

After analyzing the perceived benefits and risks associated with AI applications across six major transportation domains, a consistent pattern emerges, as illustrated in Figure 4.23. Most responses are clustered in the high-benefit, moderate-risk quadrant. This pattern indicates that transportation professionals generally view AI as a highly promising tool capable of delivering substantial improvements in areas such as asset management, safety, operations, digital twins, and generative design.

However, the survey also reveals critical exceptions to this trend. Notably, the Autonomous Vehicles domain stands out as the only domain in which perceived risks exceed perceived benefits, breaking the broader pattern observed in other areas. In fact, AVs were rated as the riskiest application area overall. This reflects a clear recognition among stakeholders that while AVs offer transformative potential, they also carry significant unresolved challenges, including safety, system reliability, and cybersecurity. Generative AI also received elevated risk scores, though still accompanied by strong benefit expectations. These exceptions highlight the need for targeted risk mitigation strategies in these emerging fields before broader deployment can be achieved.

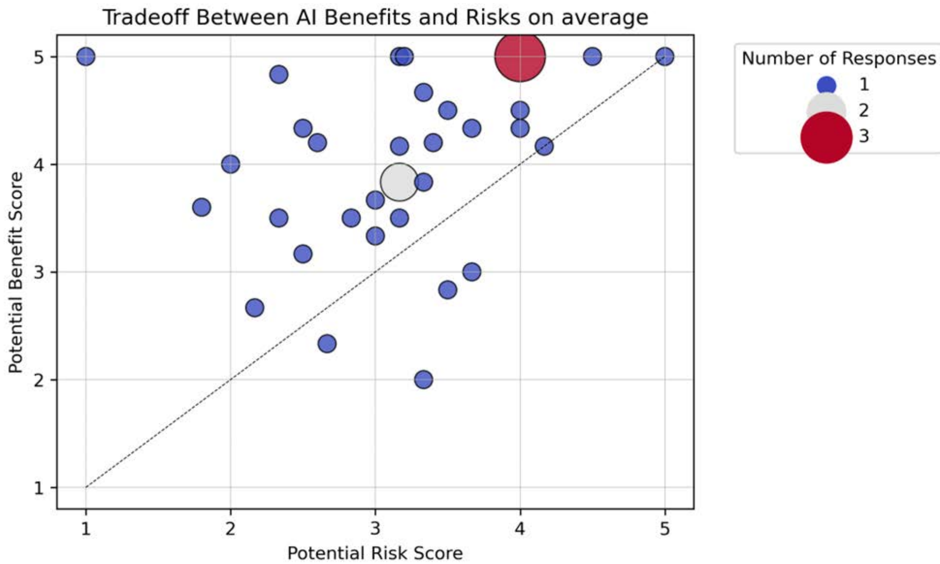

Figure 4.23 Tradeoff Analysis Between AI Benefits and Risks

Overall, the perception of respondents on the benefits and risks of AI shows enthusiasm for continued development and caution about potential challenges. While there is strong enthusiasm for the transformative potential of AI technologies, there is also clear recognition of the need for risk management frameworks, ethical oversight, and phased, evidence-driven deployment strategies.

(8) Recommendations for Future Development

To capitalize on the benefits of AI applications while addressing their risks, WisDOT should consider the following strategic actions:

- Implement a risk-benefit prioritization framework: Develop a formal evaluation matrix that scores proposed AI projects based on expected benefit magnitude and associated risk complexity. Prioritize projects in the high-benefit, moderate-risk quadrant for near-term investment, while allocating exploratory funding for high-benefit, high-risk innovations under controlled conditions.
- Phase deployment to align with maturity levels: For more mature applications (e.g., asset management, safety), move toward full-scale deployment. For less mature but high-potential areas (e.g., autonomous vehicles, generative AI), adopt a phased pilot-testing approach, building evidence of performance and addressing risks incrementally.
- Establish robust AI governance and monitoring systems: Design and implement AI governance frameworks that ensure transparency, accountability, and ethical use across all AI deployments. Set up continuous monitoring mechanisms to assess evolving risk profiles and adjust strategies accordingly.

By embracing a balanced, evidence-driven strategy, WisDOT can maximize the transformative impact of AI technologies while safeguarding public trust and ensuring system resilience.

4.2.6 Differences in Perceptions of AI Benefits and Risks by Organization Type

To better understand how institutional background may influence perceptions of AI in transportation, we divided respondents into two organizational categories: Public sector and academic/research institutions. The goal of this analysis was to examine whether these two groups differ in their views on AI applications across six key transportation domains, focusing on two core evaluation metrics: Benefit Score and Risk Score.

The analysis proceeded in three steps. First, we compared the differences of benefit and risk scores between the two organization types in each AI domain, to initially analyze the central tendency and variance in scoring patterns. Both the benefit and risk scores are based on a five-point scale, with higher score representing higher benefit or risk. Second, we conducted Analysis of Variance (ANOVA) tests to assess whether there were any statistically significant differences in the scores between the two organizational groups. Given the limitations imposed by small sample size, we also used boxplots to visualize the distribution of benefit and risk scores for each AI domain to provide a more intuitive presentation of the findings. The boxplots can be found in Appendix D.

(1) Transportation Asset Management

As mentioned before, respondents were divided into two categories: public sector and academic/research institutions. By comparing respondents' perceptions of the benefits and risks of AI in asset management, we found noteworthy differences.

In terms of AI benefits, both groups provided relatively high scores, with medians around 4, suggesting a shared recognition of the value AI can bring to infrastructure monitoring, maintenance planning, and life-cycle optimization. More pronounced, however, is the difference in perceived AI risks. Academic and research institutions consistently reported higher AI risk scores, with a median nearly one full point higher than that of public sector respondents. This discrepancy may reflect greater familiarity among researchers with the technical limitations, data governance issues, and ethical concerns surrounding AI model deployment. In contrast, public sector respondents tended to view AI as lower-risk (medians around 2.5 and 3.5 for public sector and academic/research institutions, respectively), potentially due to their exposure to well-established or vendor-supported tools, or because their evaluation frameworks prioritize operational stability over technical nuance.

(2) Transportation Safety

In the domain of transportation safety, both public sector and academic/research respondents expressed consistently high perceived benefits of AI applications. Based on survey results, the median benefit scores for both groups are comparable, centered around 4. This suggests broad agreement across sectors on the positive potential of AI for safety-related functions, including incident prediction, real-time monitoring, and driver behavior analysis. In terms of risk perception, academic/research respondents displayed slightly higher risk dispersion, with a few ratings extending to the maximum score of 5. Public sector participants provided a narrower distribution, clustering mostly around 3.5. Despite these minor differences, the overall median risk scores are similar between the groups, indicating a shared awareness of technical and implementation challenges, such as model accuracy and data integrity.

(3) Transportation Operations

In the domain of transportation operations, both public sector and academic/research organizations express generally positive perceptions of AI benefits, though some variation is observed in benefit score distribution. In our survey results, the academic/research group reports a slightly higher median benefit score, with scores clustering tightly around 4 to 5, suggesting greater optimism regarding the capacity of AI to enhance traffic flow management, real-time monitoring, and incident response. By contrast, the public sector group shows a wider spread of benefit scores, with several responses as low as 2. This dispersion may indicate a more cautious or operationally constrained perspective, possibly reflecting concerns about the readiness of existing infrastructure to support AI-based tools.

For perceived risks, both groups provide comparable assessments, with median risk scores centering around 3. The range of responses is moderately broad in both cases, though outliers appear in each group. This suggests a shared awareness of potential risks, such as data latency, algorithm opacity, or response misalignment, which can affect the real-time reliability of AI systems in traffic operations.

(4) Digital Twins

In the domain of Digital Twins, both public sector and academic/research respondents report high perceived benefits, though varying dispersion. Academic institutions provided more centralized benefit scores (mostly around 4), suggesting consistent recognition of the value of Digital Twins in infrastructure simulation, real-time monitoring, and decision support systems. In contrast, public sector responses are more widely distributed, ranging from 2 to 5, reflecting more diverse levels of familiarity or confidence in the practical implementation of Digital Twin technologies. Regarding risk perception, both groups again showed moderate to high scores, with the academic/research group reporting a slightly higher median and wider variance. While many respondents in both groups rated risk>3, some academic respondents provided outlier scores as high as 5 and as low as 1, implying a more polarized view on data integration complexity, model fidelity, and governance readiness. Public sector respondents tended to cluster around the 2-3.5 range, suggesting a more cautious but moderate evaluation of risks.

(5) Autonomous Vehicles

AVs remain one of the most debated AI application areas in transportation, and the perceptions of benefit and risk diverge notably across organization types. As a result of our analysis, respondents from academic and research institutions consistently reported higher benefit scores, with a median around 4.5, compared to a median of 3 among public sector participants. The public sector group showed greater score dispersion, including several low-end ratings (1-2), suggesting stronger skepticism or limited confidence in the practical readiness of AVs. By contrast, academic participants expressed greater optimism, likely stemming from their closer proximity to technological development and simulation research.

In terms of risk perceptions, both groups rated AV-related AI as high-risk, with median scores around 4.0 or above (with no significant differences across organization types), and considerable clustering near the maximum score of 5. This consensus could reflect shared concerns about safety validation, regulatory uncertainty, and system accountability-issues that are central to AV deployment regardless of institutional affiliation. This divergence may reflect differences in exposure: academic stakeholders may be more familiar with the long-term promise and technical milestones of AVs, while public agencies remain cautious due to short-term feasibility and policy constraints.

(6) Generative AI

Generative AI has rapidly emerged as a transformative tool across multiple sectors, including transportation, with growing interest in its potential for data synthesis, simulation, and decision support. However, perceptions of its benefits and risks differ across organizational types.

Both public sector and academic/research participants reported relatively high benefit scores for Generative AI, with medians centered around 4.0 to 4.5. Academic respondents tended to rate benefits slightly higher and showed a narrower range, suggesting a more consistently positive outlook. In contrast, the public sector group exhibited greater variability, including a subset of respondents rating benefits at the lower end (2-3), potentially indicating hesitations about practical utility or implementation barriers in government contexts. Regarding risk perceptions, both groups exhibited moderate concern. Median risk scores hovered around 3.0 for the public sector and slightly lower, near 2.5, for academic/research participants. While outliers existed in both groups (including some maximum risk ratings), the distributions generally reflected a shared but cautious stance on potential misuse, misinformation, or regulatory gaps associated with generative technologies.

Statistical analyses confirmed the absence of significant differences across organizational types. ANOVA results for benefit scores and risk scores both failed to reach statistical significance, indicating that the observed variations in perceptions are not robust enough to generalize beyond this sample.

(7) Recommendations for Future Development

To effectively navigate these sectoral differences and unlock the full potential of AI in transportation, WisDOT is advised to take the following strategic actions:

- Foster cross-sector dialogues to align expectations: Organize structured forums that bring together academic, private, and public stakeholders to share perspectives on AI benefits and constraints. Use these engagements to co-develop shared success criteria, especially for high-impact applications like autonomous systems or generative design tools.
- Bridge perception gaps through joint pilot programs: Partner with research institutions to co-lead pilot projects that translate academic innovation into applied public sector use. These collaborations can ground academic optimism in operational realities while exposing public agencies to emerging capabilities.
- Use perception data to guide AI communication strategy: Leverage these findings to tailor internal and external communication and emphasize the demonstrated value of AI to build support within skeptical stakeholder groups.

By acknowledging and strategically addressing perceptual divides, WisDOT can create a more unified, informed, and agile AI deployment ecosystem that will allow the agency to responsibly lead in the next phase of digital transformation.

4.3 Follow-up Interviews

To supplement the survey findings with real-world perspectives, 8 follow-up interviews were conducted with professionals from six organizations, including several state Departments of Transportation (FDOT, GDOT, WSDOT, TxDOT) and nationally recognized infrastructure consulting firms (HDR, Stantec). Detailed information is presented in Appendix C.

A consistent theme across interviews was the importance of beginning with clearly defined objectives. Rather than pursuing AI technologies for their novelty, interviewees stressed the need to start with specific use cases where measurable improvements can be demonstrated. Several participants emphasized that agencies benefit most when they work backward from desired outcomes and then identify how AI can support those goals.

The interviews also underscored the value of an iterative and multi-level approach to AI adoption. Agencies are increasingly combining policy development with real-time operational pilots, enabling them to learn through experience while simultaneously shaping internal governance structures. For example, some DOTs have launched pilot projects before formalizing agency-wide policies, using the outcomes to inform broader frameworks for AI integration.

Data quality and infrastructure readiness emerged as foundational priorities. Interviewees widely agreed that without accurate, well-managed, and accessible data, even the most advanced AI models cannot deliver meaningful or reliable insights. Several agencies have invested in data audits and structured data collection protocols to prepare for scalable AI applications.

Workforce development was also identified as a critical factor. Many agencies are still in the early stages of AI training and management, with some developing internal training programs while others rely on hands-on project-based learning. Interviewees highlighted that technical knowledge alone is insufficient; successful AI integration also requires cultural readiness, leadership support, and staff engagement.

Importantly, the interviews reinforced the necessity of maintaining human oversight in AI systems, particularly for safety-critical applications. While AI can support faster and more consistent decision-making, final judgments must remain with qualified personnel who understand the broader operational context. This sentiment reflects growing awareness about the risks of over-reliance on automated systems and the need for accountability in public-sector decision-making.

Finally, participants emphasized the importance of fostering diverse partnerships. Collaborations that include internal DOT teams, private-sector vendors, and academic researchers allow for both near-term implementation and long-term innovation. While vendors can accelerate deployment, academic partnerships support strategic exploration and the development of new capabilities.

Taken together, these insights point to a set of priorities that align closely with the survey findings: begin with clear goals, adopt an iterative implementation strategy, prioritize data infrastructure, invest in organizational readiness, and ensure AI applications are grounded in transparency and human oversight. By learning from the experiences of peer agencies, WisDOT can shape a balanced, forward-looking strategy that addresses both the opportunities and challenges of AI in transportation.

5. RECOMMENDATIONS AND ROADMAP

Building upon the comprehensive data analysis presented in Section 4, this chapter outlines strategic recommendations and a structured implementation roadmap for integrating AI technologies into Wisconsin's transportation systems. The recommendations are designed to address the key challenges and opportunities identified through the survey and follow-up interviews, providing WisDOT with actionable guidance for successful AI adoption across multiple time horizons and investment levels.

5.1 Comprehensive Recommendations

5.1.1 Data Management and Quality Enhancement

As revealed by the survey analyses, data quality and preparation challenges vary significantly across different data types, with text data presenting cleaning difficulties and vision data posing labeling challenges. To address these issues, we recommend that WisDOT develop or enhance the current data management strategy to standardize data collection, storage, and quality control protocols across the organization with AI adoption in sight. This should include data dictionaries, metadata standards, and quality assurance processes that ensure consistency and interoperability across all departments and systems.

The critical importance of data quality was clearly emphasized in our follow-up interviews (Section 4.3), where transportation agencies consistently highlighted data challenges as major barriers to AI implementation. As TxDOT's strategic data scientist noted, inconsistent data formats, such as 15 variations of the same highway name in databases, required extensive cleanup. Similarly, FDOT encountered challenges with underrepresented categories in training datasets that affected model performance, particularly for rare cases. These real-world experiences confirm our survey findings and underscore the need for agency-wide data governance and quality improvement initiatives to support the use of AI.

Although AI depends heavily on high-quality data to learn patterns, make predictions, and generate insights, AI can be used to improve data quality as a valuable tool. Applications include anomaly or outlier detection, feature extraction and classification, cleaning and standardizing unstructured data with NLP, missing value imputation, and multi-source data integration using machine learning models. For example, we recommend investing in transportation-specific NLP tools that can clean and structure incident reports, traveler information, and similar sources. This should include locally deployed fine-tuned Large Language Models (LLMs) that can be customized for transportation terminology and document formats while maintaining data privacy and security. Vision data labeling, identified as particularly resource-intensive, can be addressed through semi-supervised learning approaches. By implementing active learning and semi-supervised techniques, WisDOT can reduce the manual workload while maintaining annotation quality, particularly for critical applications like safety monitoring and infrastructure assessment. These approaches strategically select the most informative samples for manual labeling while using algorithmic approaches for routine cases.

5.1.2 AI Application Priorities

Initial AI applications should prioritize map and traffic data, which were identified as high-quality, low-difficulty sources in our survey. These structured data types offer the most reliable foundation for early AI implementation while delivering strong operational benefits. By building on these strengths, WisDOT can demonstrate early successes while developing capabilities for broader and more complex data types.

Asset Management applications should be accelerated as the domain with both high perceived benefits (4.1+ rating) and shorter expected timeframes. This area offers the clearest near-term opportunity for demonstrating AI value while building organizational capabilities. Applications such as predictive maintenance, automated condition assessment, and lifecycle optimization have demonstrated success in peer agencies and can provide immediate operational improvements.

Safety-focused AI systems should also receive high priority, as it emerged as another high-benefit, moderate-risk domain. Applications in crash prediction and prevention, incident detection, and data-driven safety analysis align with core agency missions while building public trust in AI technologies. These systems not only improve safety outcomes but also generate valuable data that can inform future infrastructure investments and policy decisions.

Traffic Operations represents another priority area, with the strong clustering of responses at high benefit scores indicating strong stakeholder confidence in AI's ability to improve efficiency. Adaptive traffic control, predictive traffic congestion, and real-time incident response tools can deliver visible public benefits while building DOT’s AI capabilities. These applications often benefit from existing sensor infrastructure with fewer implementation barriers.

For Autonomous Vehicle technologies, a more cautious approach is warranted given the balanced benefit-risk assessment (concentrated at benefit=5, risk=5). Rather than large-scale deployments, WisDOT should pursue a measured, phased approach through controlled pilots, simulation environments, and infrastructure readiness initiatives. This approach allows the agency to develop expertise and assess implications while minimizing risk exposure.

Generative AI presents emerging opportunities, particularly for knowledge management applications. The high benefit potential for documentation, knowledge retrieval, and scenario generation merits targeted pilot implementations in low-risk contexts. Applications such as standard operating procedure organization, design assistance, and public information management can provide valuable learning experiences while demonstrating tangible benefits.

In addition, it is essential to address urban and rural AI deployment gaps to ensure balanced spatial coverage and prevent deployment bias. Expanding data collection infrastructure through mobile sensing platforms and strategic sensor placement can extend monitoring capabilities to previously underrepresented areas, ensuring that AI applications serve the entire transportation network equitably.

5.1.3 Workforce Development and Training

Currently, our study highlighted significant gaps in AI-related training and workforce readiness across agencies, with 48.3% of respondents reporting no formal AI training and large majorities identifying technical skills (73.3%) and hands-on experience (66.7%) as critical gaps. Addressing these workforce challenges is essential for effective and strategic AI implementation. The follow-up interviews in Section 4.3.5 revealed that workforce development remains an emerging priority across transportation agencies. TxDOT's recent launch of an 'AI 101 course' covering basic concepts, machine learning, and generative AI represents a proactive approach to foundational training. However, as seen at FDOT and GDOT, many agencies still rely on informal, decentralized training with knowledge transfer primarily through hands-on project participation. The WSDOT representative's emphasis on change management and practical user training for tools like generative AI aligns with our survey's identification of technical skills and hands-on experience as the most significant gaps in the transportation workforce.

Given the large gap in AI training and other competing needs, it is important to align AI workforce development and training with WisDOT's strategic planning and budget priorities. Training effort should support agency's mission critical activities across regions and bureaus, as well as fostering the development of core competencies, knowledge skills and ability (KSA). Moreover, training initiative should focus on agency's AI capacity building through a mix of "build", "buy" or "rent" approaches with the appropriate allocation of training resources and personnel.

We recommend a tiered AI training program that includes training curricula for employees at different career stages with varying AI exposure. Senior employees should receive training focused on strategic oversight, ethical governance, and AI integration with existing systems. Mid-career professionals need hands-on modeling, tool proficiency, and project implementation skills. Early-career staff require foundational technical skills, data management principles, and application-specific toolkits. This differentiated approach recognizes the diverse roles and responsibilities across the organization.

We support the development of training tasks with work experience because satisfaction with AI applications varies significantly by work experience. Highly experienced employees (>10 years) should lead deployments in mature AI domains like Asset Management, where their institutional knowledge ensures stability. Mid-career professionals (5-10 years) can serve in cross-domain coordination roles, while early-career employees (<5 years) can drive innovation in emerging applications like Generative AI. This approach maximizes the value of diverse perspectives and experiences.

We suggest targeted interventions to address the AI trust gap between employees with different AI-to-work experience ratios. Field demonstrations and case studies can showcase AI performance for experienced professionals skeptical of newer technologies. Explainable AI features and simplified dashboards can support specialists who are less familiar with AI models. Mentorship programs pairing AI-fluent staff with domain experts can facilitate knowledge transfer and build mutual understanding. Beyond formal training, practical learning opportunities through hands-on project experience, hackathons, and cross-functional innovation teams allow employees to apply AI skills to real transportation challenges. These experiential learning approaches complement classroom instruction and help build the practical capabilities identified as lacking in the survey.

Finally, establishing an AI Center of Excellence would create a dedicated team of AI experts who can provide internal consulting, training, and project support across the organization. While primarily composed of internal DOT personnel, including technical experts and domain specialists familiar with transportation use cases, the Center could also engage external advisors from academia or industry on a periodic basis for strategic guidance. The Center would serve as the operational backbone of AI efforts across the agency and act as a key coordination node, interfacing with both the AI Ethics Committee and the Transportation AI Research Consortium to align implementation with ethical standards and research insights.

5.1.4 Policy and Governance Framework

The survey and follow-up interviews highlighted the importance of robust governance frameworks for successful AI integration. With 66.7% of survey respondents endorsing AI-specific policies as a priority action and 59.3% emphasizing security and ethical concerns, governance must be a foundational element of WisDOT’s AI strategy.

An AI Ethics Committee could be established as a cross-functional body responsible for developing ethical guidelines, reviewing high-risk applications, and ensuring alignment with public values. This committee should include representatives from technical, legal, operational, and community engagement teams to ensure diverse perspectives inform governance decisions. Regular review cycles and transparent processes will build trust in AI applications both internally and externally. To streamline structure and ensure cohesion, the Ethics Committee could operate as a subcommittee within the broader Transportation AI Research Consortium, ensuring alignment with broader strategic and research goals.

A comprehensive AI policy should address data privacy and security protocols, model documentation and transparency requirements, testing and validation standards, human oversight mechanisms for critical systems, and explainability requirements for different application types. This policy framework provides clear guidelines for development teams while ensuring consistency across the organization. It should evolve over time as technologies mature and new challenges emerge.

Implementation of a risk-benefit assessment framework would provide a structured process for evaluating proposed AI projects based on expected benefits, potential risks, data requirements, and implementation complexity. This framework should guide resource allocation and prioritization decisions, ensuring that investments align with organizational priorities and risk tolerance. Regular reviews of project performance against expectations can inform refinements to the assessment process.

Our follow-up interviews provided valuable insights into evolving governance approaches. Several interviewees described implementing specialized AI policies, with one consultant noting requirements that “anything output from AI has to be quality controlled” and another mentioning policy against “uploading sensitive information” to language models. Data privacy emerged as a particular concern, with GDOT avoiding video recording to mitigate personally identifiable information risks, while WSDOT discouraged the use of external tools like ChatGPT due to data leakage concerns. These practical approaches from peer agencies provide valuable models as WisDOT develop its own framework.

Also emphasized in these follow-up interviews is the responsible AI-human collaboration that requires maintaining appropriate human oversight in all AI implementations, particularly for safety-critical applications. Clear decision authority boundaries between automated systems and human operators must be established, with escalation protocols for edge cases and unexpected situations. This approach balances efficiency gains with safety considerations.

Model management processes should be established for versioning, performance monitoring, drift detection, and retraining to ensure AI systems remain effective and trustworthy over time. These governance mechanisms recognize that AI systems are not static deployments but evolving capabilities that require ongoing monitoring and maintenance. Regular audits and performance reviews can identify issues before they impact operations.

5.1.5 Collaboration and Partnership Models

WisDOT has already engaged in a range of AI-related partnerships, including vendor collaborations, peer agency exchanges, academic engagements, and participation in national networks such as TRB and AASHTO initiatives. These efforts support capability building and knowledge sharing.

To further strengthen these foundations, we recommend establishing a Transportation AI Research Consortium in partnership with Wisconsin universities, technology companies, and public agencies. This consortium would serve as a formal platform for identifying emerging AI opportunities, conducting joint research, sharing datasets and tools, and piloting transportation-specific AI applications. It would be composed of academic researchers, DOT experts, and private-sector partners working toward shared goals. To maximize impact and avoid redundancy, the Consortium could host the AI Ethics Committee as a standing subcommittee and maintain regular coordination with the AI Center of Excellence.

5.2 Implementation Roadmap

To guide WisDOT's AI adoption over time, Figure 5.1 outlines a phased implementation roadmap across short-, medium-, and long-term horizons. The roadmap emphasizes manageable progress, focusing on foundational priorities early on and scaling up as capacity grows.

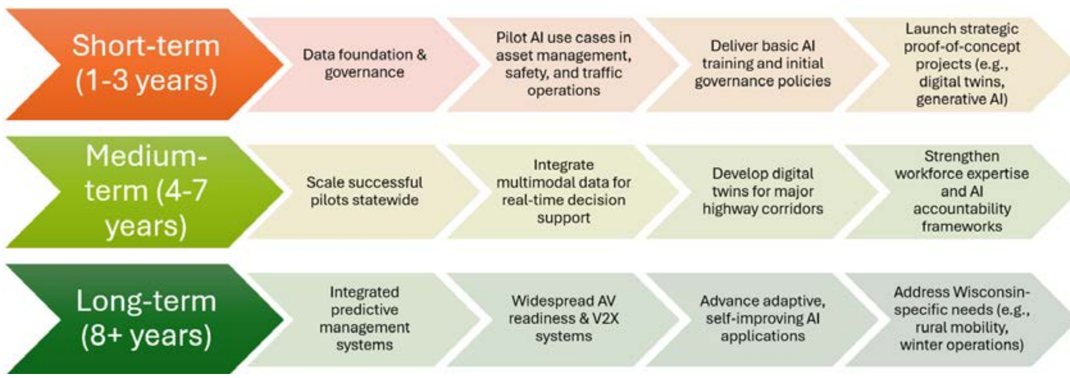

Figure 5.1 WisDOT AI Implementation Roadmap

5.2.1 Short-term Implementation Plan (1-3 years)

Building on the survey findings that identified Asset Management, Transportation Safety, and Traffic Operations as domains with high benefit potential and shorter implementation timeframes, the short-term plan focuses on these areas while establishing foundational capabilities.

The first year should emphasize establishing data foundations through a comprehensive data asset inventory and quality assessment. Standardized data collection protocols for high-priority data types should be developed, with basic data cleaning and preparation pipelines implemented to support initial applications. Data governance structures and quality monitoring processes will provide the framework for sustainable data management practices. This foundation is essential, as the survey findings clearly identified data quality as a key to successful AI implementation.

In years one and two, proof of concept applications should be discussed and identified in high-value areas and/or near-term highway or traffic projects: automated asset inventory using computer vision, predictive maintenance tools for critical infrastructure components, machine learning for traffic pattern analysis and basic prediction leverages existing data streams for immediate benefits, NLP for automated incident report classification and trend analysis. The follow-up interviews in Section 4.3.2 identified several successful early-stage AI implementations that could serve as models for WisDOT. For traffic operations, Las Vegas's implementation of the Derq system uses video cameras and edge computing at intersections to "improve safety and reduce delay by approximately 20%". In asset management, TxDOT has used connected vehicle data to predict battery failures with 96% accuracy, enabling proactive maintenance scheduling. FDOT's progress in pavement condition forecasting through machine learning for raveling detection demonstrates the feasibility of incremental improvement through multiple iterations. These practical examples provide valuable reference points for WisDOT's initial implementations.

Three to five strategic pilots in years two and three allow for controlled experimentation with more advanced applications. Testing advanced traffic management systems in selected urban corridors demonstrates value in visible public-facing applications. Automated safety monitoring at high-risk intersections directly addresses critical safety priorities. Testing generative AI for a standard operating procedure organization provides a low-risk experience with emerging technologies. Initial digital twin prototypes for limited infrastructure segments lay the groundwork for more comprehensive implementations later.

By year three, performance baselines should be established through metrics and monitoring for deployed AI systems. Documenting operational improvements and efficiency gains builds the case for investment, while assessing workforce skills development identifies remaining gaps to address. Governance processes can be refined based on early implementation experience, ensuring they remain effective.

Organizational capacity building should span the entire short-term period, with basic AI literacy training for 50% and advanced training for 25% of relevant staff. The AI Center of Excellence should be established with initial technical specialists who can support early implementations and knowledge transfer. Draft AI governance policies and ethics guidelines will provide the framework for responsible development, while initial risk assessment frameworks for AI project evaluation ensure alignment with organizational priorities and values.

5.2.2 Medium-term Development Plan (4-7 years)

The medium-term plan expands AI implementation to more complex domains while enhancing existing applications and addressing the underlying capabilities identified as priorities in our survey.

In years four and five, successful applications from the short-term phase should be scaled up and incorporated into selected projects or operational areas identified in the short-term stage, moving from pilots to production. Integration of AI systems with existing transportation management platforms ensures operational cohesion and data sharing. More sophisticated predictive models can be developed using the expanded historical data collected during early implementations. Automated decision support for routine maintenance planning can deliver efficiency gains while building trust in AI-assisted processes.

Data integration advances in years four through six should focus on developing multimodal fusion capabilities that combine vision, text, and sensor data for comprehensive situational awareness. Real-time data streams for dynamic decision support enable more responsive operations, while automated validation and enrichment processes improve data quality at scale. Edge computing capabilities for distributed data processing support applications in remote locations and reduce central processing requirements.

Application scope expansion in years five through seven should include comprehensive digital twin environments for major highway corridors, providing powerful simulation capabilities. Advanced generative AI applications for planning and design can accelerate project development while improving outcomes. Sophisticated safety analytics integrating multiple data sources enable more proactive risk management. Limited testing of autonomous vehicles on open roads prepares for future mobility.

Governance and ethics frameworks should be strengthened in years six and seven through comprehensive AI accountability mechanisms that ensure responsible use. Enhanced explainability features for complex AI systems support user trust and regulatory compliance. Community engagement on AI deployment ensures public perspectives inform development priorities.

Workforce development should continue throughout the medium term, potentially including the creation of certificate programs, new career pathways and development of robust knowledge management practices. Establishing career development pathways for AI-focused transportation professionals will help recruit and retain specialized talent. Formal knowledge transfer mechanisms between technical and domain experts can bridge organizational silos and ensure that AI applications align with the agency's operational needs. Basic AI literacy training will cover 100% relevant staff, and advanced training programs will be continuously developed and delivered to the most relevant staff.

5.2.3 Long-term Vision (8+ years)

The long-term vision focuses on advancing foundational technologies identified in the survey as having high potential but requiring longer implementation timelines, including autonomous vehicles and digital twins.

By years eight to ten, WisDOT should aim to build more integrated transportation systems that support data-driven decision-making and predictive capabilities across key domains. Digital twins may enable enhanced planning and simulation, while adaptive infrastructure can help improve operational efficiency. Support for autonomous vehicle integration is expected to grow, with attention to infrastructure readiness and communication between vehicles and transportation assets. Progress in AI-supported multimodal coordination and smart corridors may help alleviate congestion and expand mobility options.

Beyond year ten, the focus shifts to maintaining system adaptability and resilience. Potential initiatives may include predictive maintenance tools, expanded data sharing across regions, and AI-enhanced service planning to ensure equitable access in both urban and rural areas.

Finally, WisDOT should continue exploring opportunities to apply transportation AI to Wisconsin-specific challenges, such as winter operations and rural mobility, while contributing to broader national progress through research and policy development.

5.3 Success Metrics and Evaluation Framework

To track progress and demonstrate value, we recommend leveraging AI evaluation with WisDOT's MAPSS Performance Program. The MAPSS Program consists of thirty individual performance measures centered around five core goals: Mobility, Accountability, Preservation, Safety, and Service. This framework combines outcome-based metrics that track tangible improvements and perception-based metrics that monitor organizational readiness.

5.3.1 Outcome-Based Metrics

Outcome-based metrics evaluate how AI technologies deliver measurable progress across MAPSS goals:

- **Mobility**: Reduced congestion and improved travel time reliability in AI-managed corridors; increased throughput at key intersections; decreased emissions from idle time.
- **Accountability**: Operational cost reductions; automated workflows leading to staff time savings; more accurate resource allocation.
- **Preservation**: Improved asset condition ratings; reduced unexpected failures; cost savings from predictive maintenance; extended asset lifespan.
- **Safety**: Fewer crashes and reduced severity at AI-monitored sites; faster incident response times; improved hazard detection.
- **Service**: Higher user satisfaction; improved accessibility; reduced service delays; better public perception of transportation quality.

5.3.2 Perception-Based Metrics

To complement technical outcomes, we propose a biennial Organizational Readiness Metrics Survey to assess internal capacity and stakeholder confidence:

- **Workforce Readiness**: Staff AI training rates, perceived training effectiveness, and reduction in skills gaps.

- **Data Preparedness**: Improvements in data quality, accessibility, and usability; reduced data preparation time.
- **Governance Maturity**: Implementation of AI policies; staff awareness of governance and ethics; internal compliance rates.
- **Collaboration Effectiveness**: Number and success of external partnerships; interdepartmental knowledge sharing; participation in AI communities.

This mixed-methods framework ensures WisDOT can track both the practical impacts of AI and the organizational maturity required to sustain progress. It supports adaptive management, encourages transparency, and aligns AI development with MAPSS priorities.

6. CONCLUSIONS

6.1 Key Findings

Table 6.1 presents key findings of this work, including adoption trends, data and skill challenges, high-potential application areas, and recommended actions.

Table 6.1 Summary of Key Findings

Theme	Key Findings	Implications
AI Adoption Maturity	70.8% of professionals have <5 years of AI experience.	AI adoption is early stage with phased strategies.
Data Quality & Type	Map & Traffic data are high-quality and low difficulty. Text and Vision data needs cleaning and labeling.	Start with structured data; invest in tools for text and vision processing.
Skills Gaps	73.3% reported technical skills gaps; 50.0% cited data management as a challenge.	Upskilling and hiring for technical and data roles.
High-Potential Application Areas	Asset management, safety, and traffic operations offer high benefit and short timelines.	Focus early AI efforts in these domains.
Autonomous Vehicles	Rated as relatively high benefit but long implementation horizon and highest risk.	Requires a long-term, staged approach and plans to mitigate risk.
Training Effectiveness	48.3% had no formal AI training; only 17.2% rated it highly effective.	Improve and expand training programs.
Recommended Actions	77.8% support AI training; 66.7% endorse AI-specific policy and data system improvements.	Build internal capacity and governance frameworks.

6.2 Implications and Prioritized Recommendations

Our highest-priority recommendations for WisDOT include:

1. **Establish comprehensive data governance frameworks** that standardize collection, storage, and quality control protocols across the organization. This foundation is essential as data quality consistently emerges as a prerequisite for successful AI implementation.

2. **Prioritize Asset Management, Safety, and Operations applications** for initial AI deployments. These areas offer the clearest near-term opportunities for demonstrating AI's benefits while building organizational capabilities.
3. **Implement AI training programs** that develop differentiated skills for employees at different career stages and with varying AI exposure. This approach could address the workforce gaps identified in the survey and maximize the value of diverse perspectives and experiences.
4. **Establish AI Center of Excellence** to create a dedicated team of AI experts who can provide internal consulting, training, and project support across the organization. The Center would serve as the operational backbone of AI efforts across the agency and act as a key coordination node, interfacing with both the AI Ethics Committee and the Transportation AI Research Consortium to align implementation with ethical standards and research insights.
5. **Develop robust AI governance policies** that address data privacy, model documentation, testing standards, and human oversight mechanisms. Clear governance frameworks provide guidelines for development teams while ensuring responsible innovation.
6. **Pursue a diversified partnership strategy** that leverages vendor relationships for proven solutions, academic collaborations for research, and peer agency exchanges for knowledge. This balanced approach accelerates capability development while managing resource constraints.

6.3 Implementation Roadmap

A summary of the phased AI implementation roadmap, along with tailored strategies, is provided in Table 6.2 to guide WisDOT's planning and prioritization across time horizons.

Table 6.2 WisDOT AI Implementation Roadmap Overview

Timeline	**Strategic Focus**
Short-term (1–3 years)	• Establish data foundations • Deploy proven AI in asset management, safety, operations through small-scale, pilot applications • Build organizational capacity
Medium-term (4–7 years)	• Scale successful applications at selected locations • Advance data integration and fusion • Develop domain-specific expertise • Expand to digital twins and advanced safety analytics

Long-term (8+ years)	• Integrated predictive management systems • Comprehensive digital twins • Infrastructure for AVs • Advanced multimodal mobility solutions

In the short term (1-3 years), WisDOT should focus on establishing data foundations, deploying proven AI applications in high-value areas using pilot studies, building organizational capacity, and conducting strategic pilots to gain experience with more advanced technologies. Second, the medium-term plan (4-7 years) expands successful applications statewide, advances data integration capabilities, enhances workforce expertise, and expands into more sophisticated applications like digital twins and advanced safety analytics. This phase bridges initial implementations with a longer-term vision. Lastly, the long-term vision (8+ years) aims for fully integrated transportation management systems with sophisticated predictive capabilities, comprehensive digital twins, infrastructure readiness for autonomous vehicles, and advanced mobility solutions. This vision represents the culmination of WisDOT's AI journey, positioning the agency as a leader in transportation innovation.

6.4 Broader Impacts, Next Steps, and Study Limitations

The integration of AI into transportation systems represents a transformative opportunity to enhance safety, efficiency, and sustainability across Wisconsin's transportation network. By implementing the recommendations in this report, WisDOT can build the foundational capabilities needed to harness this potential while managing associated risks and challenges. Furthermore, while this study offers a comprehensive strategic framework and implementation roadmap, a detailed analysis of future investment levels (e.g., specific dollar amounts or precise budget allocations for the various AI application areas) was considered beyond the defined scope of this current research phase. Such detailed financial planning would form a subsequent stage of work.

Moving forward, if a Phase II project is initiated, it will build on the insights from this report to translate high-level strategies into detailed implementation pathways. Phase II will focus on collecting more targeted and granular data from internal WisDOT operations, external stakeholders, and emerging AI vendors to inform use-case-specific feasibility and readiness. It will also support the development of technical prototypes, internal workforce engagement strategies, and policy alignment mechanisms to operationalize AI adoption at scale. In addition, more investment suggestions will be given after this work to collect relevant budget information from other regions.

Proposed Phase II Plan:

Building on the findings of Phase I, Phase II could explore a range of strategic activities to further assess and advance the role of AI within WisDOT. Recognizing that not all components may be achievable within a single year, the following items represent potential areas of exploration and prioritization:

- Conduct in-depth case studies on high priority use cases identified in Phase I.
- Expand data collection to include: (a) Internal WisDOT operational datasets to evaluate AI-readiness. (b) Feedback from frontline staff and local partners to validate practical deployment challenges. (c) Landscape scan of AI vendors and technologies applicable to WisDOT needs.
- Develop initial AI implementation prototypes in collaboration with WisDOT units.
- Establish evaluation criteria and metrics for monitoring AI deployment outcomes across technical and operational dimensions.
- Co-design a workforce development roadmap with internal HR and training departments to close identified skill gaps.
- Initiate cross-agency collaboration forums to align data-sharing, ethical standards, and procurement strategies.
- Refine the AI implementation roadmap by incorporating Phase II findings into a detailed, year-by-year action plan for multiple investment scenarios.
- Collect comparative survey data from other U.S. states and international transportation agencies to benchmark AI adoption practices and investment models. These insights will support the development of context-specific funding strategies tailored to WisDOT’s operational landscape and policy environment.

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8. APPENDIX

APPENDIX A: FULL LITERATURE REVIEW

1. Data Sources

This task employed a diverse array of reputable and specialized data sources in conducting the literature review. We aimed to ensure a thorough coverage of academic research and industry practices, capturing the multifaceted nature of AI's application in transportation. The following section details the data sources, explaining their significance and contribution to our research.

Google Scholar served as our primary gateway to academic literature. It provided access to a vast array of peer-reviewed articles, conference papers, and academic publications across multiple disciplines. It allowed us to discover connections between AI and transportation, ranging from asset management to autonomous vehicles. Moreover, to delve deeper into transportation-specific research, we utilized the Transport Research International Documentation (TRID) database. TRID is the world's largest and most comprehensive bibliographic resource on transportation research information. With access to over 1.25 million records of transportation research worldwide, including journal articles, books, technical reports, and conference proceedings, TRID provided us with a wealth of specialized knowledge. This database was instrumental in identifying trends, challenges, and innovations specific to AI applications in transportation across different agencies. Lastly, the National Transportation Library Repository & Open Science Access Platform played a crucial role in our understanding of government-funded research and initiatives. This platform provides access to research results and data sponsored by the U.S. Department of Transportation. It offered valuable insights into federal perspectives on AI in transportation, including policy considerations, funding priorities, and large-scale implementation projects. The inclusion of this source ensured that our review captured not only academic and industry viewpoints but also governmental strategies and initiatives.

By leveraging this diverse array of authoritative sources, we aimed to capture a comprehensive and nuanced view of the current state, trends, and future directions of AI applications in transportation. Our multi-faceted approach, combining insights from academic research, government initiatives, industry innovations, and technical publications, provides a holistic understanding of the field. This thorough and varied data collection strategy ensures that our literature review offers a robust foundation for understanding the complex and rapidly evolving landscape of AI in transportation.

2. Search Strategies

The literature review employed a comprehensive and systematic search strategy designed to capture the breadth and depth of this rapidly evolving field. The strategy was carefully crafted to ensure thorough coverage while maintaining focus on the most relevant and impactful research. This section outlines our approach to identifying, filtering, and selecting the literature for review.

We began by developing a set of key search terms and phrases that encompassed the intersection of artificial intelligence and transportation. These terms were carefully selected to capture a wide range of AI technologies and their applications across various transportation domains. Our primary search string included combinations of AI-related terms (e.g., "artificial intelligence," "machine learning," "deep learning," "computer vision", "natural language processing") with transportation-specific terms (e.g., "transportation," "traffic management," "public transit," "logistics," "autonomous vehicles"). We also included more specific phrases such as "transportation asset management," "digital twins in traffic," and "safety in transportation" to capture domain-specific applications.

To ensure comprehensive coverage, we employed both broad and narrow search strategies. The broad strategy used general terms to capture a wide range of literature, while the narrow strategy utilized more specific combinations to focus on applications or technologies. For example, a broad search might use "artificial intelligence AND transportation," while a narrow search could be "deep learning AND traffic signal optimization." We conducted our searches across the previously mentioned databases, adjusting our search strings as necessary to accommodate the specific syntax and capabilities of each platform. Boolean operators (AND, OR, NOT) were used to refine searches and combine different concepts. For instance, we might use a search string like: (("artificial intelligence" OR "machine learning") AND ("transportation" OR "traffic") NOT ("air traffic control")).

To ensure the relevance and currency of our review, we primarily focused on literature published within the last five years (2019-2024). However, we did not strictly limit our search to this timeframe, as some seminal works or foundational studies from earlier years were also included when deemed highly relevant or influential to the field. Language filters were applied to limit results to English publications, as this language encompasses a significant portion of global research in this field and aligns with the linguistic capabilities of our research team. By employing this comprehensive and multi-faceted search strategy, we aimed to capture a broad and representative sample of the current research and applications of AI in transportation. This approach allowed us to synthesize insights from various sources, providing a holistic view of the field while maintaining a focus on the most relevant and impactful developments.

3. Analysis Approach

Our analysis approach for this literature review on AI applications in transportation has been meticulously designed to achieve three primary objectives: (1) identifying current applications of AI in transportation, (2) determining key questions for surveying DOTs and related institutions, and (3) checking for existing answers to potential implementation challenges. This focused strategy lays the groundwork for subsequent interviews with DOT personnel and other relevant stakeholders, ultimately leading to the development of future recommendations for AI implementation in our state's DOT.

We began our analysis by systematically categorizing the AI applications found in the literature. This categorization process involved classifying applications based on specific transportation domains such as traffic asset management, transportation safety, and transportation operations. Simultaneously, we categorized the AI technologies used, noting whether applications employed ML, computer vision, natural language processing, generative AI, or other AI techniques. We also paid close attention to the implementation stage of each application, distinguishing between theoretical proposals, pilot projects, and fully implemented systems. The geographical context of these implementations was carefully recorded, with a particular focus on state-level DOT initiatives. This comprehensive categorization allowed us to create a detailed map of current AI applications in transportation, identifying both common trends and innovative approaches. Figure A1 shows the distribution of papers and reports we reviewed.

To prepare for our interviews with DOT personnel and related agencies, we conducted a thorough gap analysis. This process involved identifying areas where the literature provided comprehensive information and contrasting them with areas of limited coverage. We noted discrepancies or conflicting information in the literature that would require clarification from practitioners. Additionally, we highlighted innovative applications that, while not widely adopted, could be of particular interest to our state's DOT. This gap analysis directly informed the development of our interview questions, ensuring that we address both well-documented areas and potential blind spots in the current literature.

Throughout our review, we paid particular attention to implementation challenges and solutions mentioned in the literature. We categorized common challenges, such as data quality issues, integration with legacy systems, and workforce skills gaps. Alongside these challenges, we compiled successful strategies and best practices for overcoming them. Importantly, we identified areas where challenges persist without clear solutions, marking these as key points for further investigation during our upcoming interviews. This synthesis helps us anticipate potential hurdles in AI implementation and prepare targeted questions about overcoming these obstacles.

As a final step, we synthesized our findings to prepare for the interview phase. We developed a list of key topics and questions to explore with DOT personnel based on gaps and interesting findings from the literature. We prepared summaries of relevant case studies and best practices to potentially share and discuss during interviews. Additionally, we identified areas where the literature suggests promising applications but lacks real-world implementation data, marking these for specific inquiry during interviews.

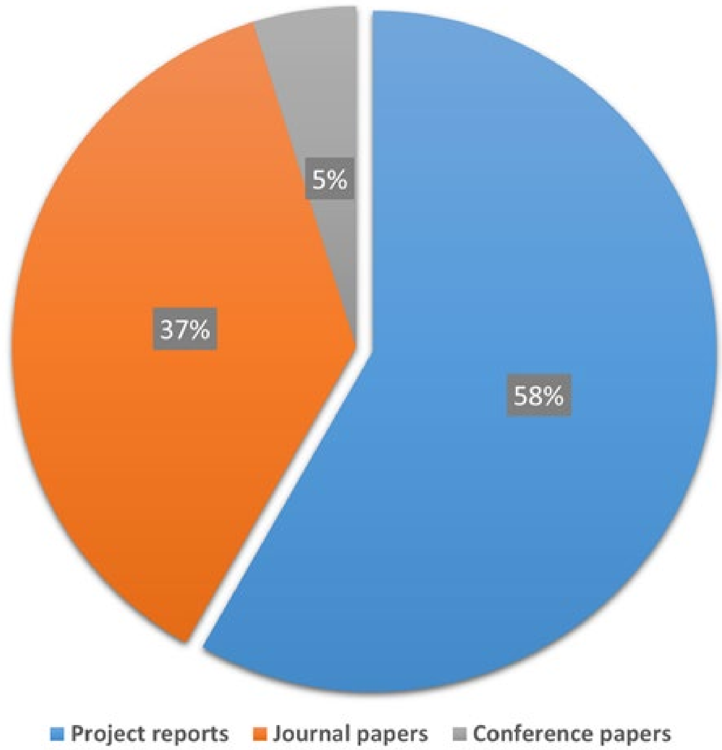


Figure A1 Types of Papers and Reports in the Literature Review.

4. AI-based Applications in Transportation

Transportation Asset Management

Transportation asset management focuses on optimizing infrastructure upkeep by improving decision-making related to resource distribution. It involves a structured approach that helps agencies determine where to invest funds for maximum long-term benefits [1]. It consists of an inventory and assessment, performance management, life cycle cost analysis, risk management, prioritization and optimization, and sustainability and resilience of transportation infrastructure assets, including roads, bridges, tunnels, and transit systems [2]. AI can enhance the efficiency, accuracy, and safety of the asset management procedure. For example, vehicles equipped with cameras and laser systems can collect and automatically analyze road infrastructure data while traveling at regular speeds. When combined with GPS, distance measurements, and AI-based annotation, the systems can reduce safety concerns and human error. AI can also compare data in real time with existing databases to produce reports on asset conditions and recommend maintenance. This approach saves time and enhances precision, offering a clearer view of infrastructure. Furthermore, AI can analyze historical data, such as weather and traffic patterns, to predict future conditions, potential asset failures, and the effectiveness of repairs, leading to more strategic planning and maintenance.

Pavement management systems are widely regarded as essential tools for transportation agencies to maximize available funding, effectively communicate budget requirements, and manage their pavement networks more objectively [3]. Over the past decade, many highway agencies have adopted 3D laser-based pavement imaging systems to automate pavement condition assessments. Additionally, 2D imaging technologies and smartphones are frequently employed for pavement evaluations, especially by local agencies. These collected pavement images are then used to extract pavement distresses semi- or fully-automatically through various methods [4]. Unmanned aerial systems (UAS) are also increasingly utilized to enhance asset management and inspection processes, with their three-dimensional point cloud data and high-resolution videos offering rich information [5]. To process this, ML techniques, including neural networks and image processing algorithms, are used to analyze 3D point clouds and extract key features and insights [6]. For instance, Texas DOT is working on developing an automated system for pavement condition assessment using ML and AI in computer vision. This initiative aims to overcome the limitations of manual quality assurance and the reliance on proprietary vendor data. This will help TxDOT improve the quality of its automated pavement condition data, ultimately leading to better pavement performance across the state [7]. Back in 2017, Texas DOT used Google's Vertex AI to analyze raw data on pavement cracks and conditions gathered using LiDAR technology that was mounted on specially fitted agency vehicles. Google's Auto Machine Learning "object tracking" and "classification" features helped them categorize pavement conditions on a scale of one to ten. The time needed to complete the project has been reduced by 30 to 70 percent. Similarly, Georgia DOT, which collaborated with Georgia Tech, has implemented automatic pavement crack detection and classification using ML and deep learning [8]. They are also using low-cost mobile devices and AI to analyze traffic signs around potentially dangerous curves [9]. This implementation of automatic sign inventory can help the DOT improve safety and reduce crashes at road curves [10]. Moreover, researchers from academic institutions are working on using data-driven intelligence technologies to conduct deep data analysis on existing pavement data and create predictive models for pavement performance, material properties, traffic effects, and pavement maintenance plans. The prediction model is expected to support State DOTs in their transportation infrastructure asset management practices [11].

The project funded by Florida DOT has shown an advanced methodology to gather roadway geometry data more quickly, safely, and cost-effectively. The research uses Computer Vision and Deep Learning techniques to detect turning lane pavement markings from high-resolution aerial images. When implemented in Leon County, the average accuracy of identifying turning features has reached 87% with a 25% confidence threshold [12]. It can help state DOTs identify deteriorated markings, compare turning lane positions with other roadway features like crosswalks, and analyze intersection-related accidents.

FHWA is exploring how AI can be utilized to gather and process data, potentially revolutionizing winter maintenance operations by improving safety, mobility, and cost-efficiency while also reducing labor demands and optimizing pavement design and management. Researchers from academic institutions are leading a project to enhance traditional model-based winter maintenance with an AI-powered system capable of real-time data analysis for autonomous decision-making, continuously refining its performance as more data becomes available [13]. For example, Recurrent Neural Networks (RNN) can be used to predict critical variables like salt concentrations and surface temperatures more accurately than traditional empirical models. By analyzing historical and real-time data, RNNs offer improved road condition forecasting, enabling better preparation for winter storms. Deep Reinforcement Learning (DRL) algorithms can optimize decisions for salting and snow removal based on real-time conditions, such as traffic flow and weather data. These systems "learn" over time, improving their decision-making ability with each storm. DRL can analyze the cost-effectiveness of actions and maximize safety while minimizing costs. Convolutional Neural Networks (CNN) can process visual data from surveillance cameras or truck-mounted cameras, providing real-time insights into pavement and weather conditions. By integrating video data, CNNs can improve the accuracy and timeliness of road assessments, surpassing traditional data sources like weather stations and Road Weather Information System (RWIS).

Other potential applications of AI in asset management include bridge visual inspections and bridge structural diagnosis [2]. Bridge visual inspections are conducted by transportation agencies generally. The bridge inspectors must visit the bridge, perform several tests, and register the type and severity of the damage. This process is labor-intensive and costly. To address this, industries are now adopting automated visual inspection techniques that use robots and computer vision to detect and quantify damages like cracks. For instance, CNN, a powerful classification tool, has been applied in Structural Health Monitoring (SHM) to detect surface defects [14]. AI algorithms can be trained to identify various types of damage, such as cracks, reinforcement corrosion, and moisture. Oklahoma State University and Oklahoma DOT are developing advanced machine-learning-based algorithms to detect different damage modes of the girder. The implementation of the system can facilitate damage detection and performance assessment of steel bridge girders under fatigue effects [15]. Virginia DOT is exploring the use of AI, augmented reality (AR), and virtual reality (VR) to assess the condition of its 21,000 bridges and culverts [16]. AI is applied to automatically detect and quantify defects such as cracks, delamination, spalls, and steel corrosion, simulating human visual perception. The integration of these technologies can significantly speed up the assessment process by recognizing patterns of deterioration and tracking changes over time. Additionally, AI can assist in structural analysis when some bridge data is incomplete. Inspection data typically comes in qualitative forms, which can be challenging to interpret for structural safety assessments. AI tools help automatically or semi-automatically extract quantitative information from inspection records, such as images, diagrams, and notes. By incorporating data from historical inspections, AI fills in missing information to provide a more comprehensive assessment of the bridge's condition.

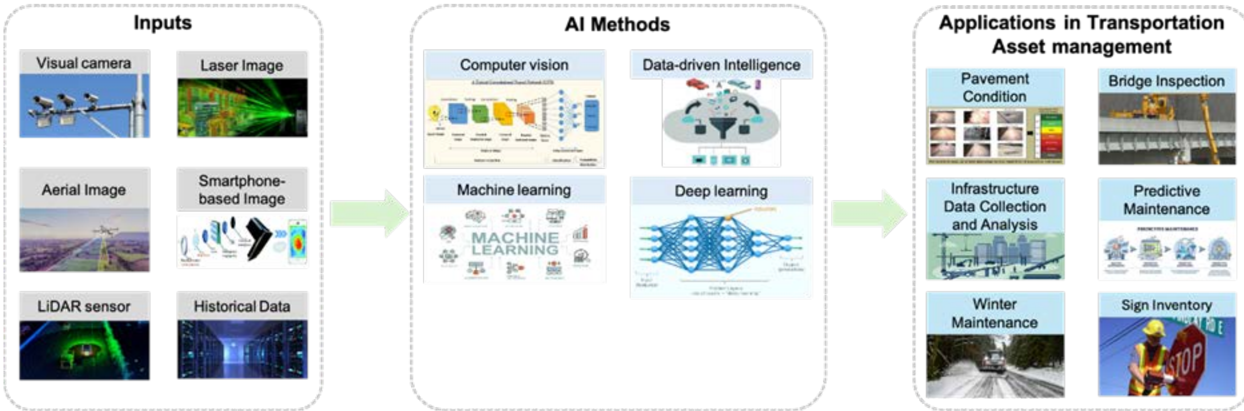


Figure A2 AI-Driven Methods and Applications for Transportation Asset Management.

In general, the benefits of AI applications in transportation asset management (Figure A2) are summarized as follows. First, AI enhances the efficiency and accuracy of infrastructure assessments, especially for bridges and pavements. AI helps detect, quantify, and track defects and provide real-time condition assessments, reducing the need for frequent on-site inspections. Second, AI-powered systems combined with technologies like 3D imaging, drones, and laser scanning allow for efficient, automated data collection and analysis. These systems can capture large volumes of data and compare it against historical databases to recommend timely maintenance actions, improving both precision and safety. Third, AI can analyze historical data on weather, traffic, and previous inspections to predict potential infrastructure failures. This enables proactive maintenance, optimized resource allocation, and a better understanding of deterioration mechanisms over time, which supports long-term planning. Lastly, by automating reporting and providing real-time insights, AI facilitates collaboration among engineers and inspectors. It helps agencies make better decisions faster, reducing the cost and time associated with infrastructure maintenance and minimizing disruptions to the traveling public.

However, potential barriers to AI application in transportation asset management exist as well. Currently, vendors tend to focus on asset management solutions for pavements and bridges, but they have yet to fully adopt management software that supports decision support systems (DSS) [17]. Secondly, sensors sometimes provide inaccurate data and have sparse coverage. Precise weather data for urban areas is lacking, making it harder to rely on sensor-driven AI analysis. Also, developers may lack access to sufficient and high-quality data for running AI algorithms. As AI continues to evolve, there will also be a need for workforce training in AI technologies and advanced data analytics. Staff must also be educated on the safe use of UAS and other new systems and devices.

Transportation Safety

AI has emerged as a transformative force in enhancing transportation safety, offering innovative solutions to long-standing challenges in accident prevention, emergency response, and overall risk management. The applications of AI in this domain span a wide spectrum, from predictive analytics for identifying high-risk areas to real-time monitoring systems that can detect and respond to safety threats instantaneously.

In the realm of academic research, institutes have been exploring cutting-edge AI technologies to push the boundaries of transportation safety. In driver behavior analysis, researchers have employed deep learning methods to monitor drivers' involvement in secondary tasks [18], providing real-time insights into potential distractions. CNNs and Long Short-Term Memory (LSTM) networks have been utilized to predict driving behavior based on eye gaze patterns [19], [20] , offering a non-intrusive method for assessing driver attention. Advanced ML algorithms have been applied to identify drowsy and distracted driving using vehicle motion parameters [21], [22], enabling early detection of unsafe driving conditions. Additionally, logistic regression models have been used to study the impact of mobile phone use on driving [23], quantifying the risks associated with this common distraction.

For pedestrian safety, researchers have utilized logistic regression models to examine the complex relationship between unsafe pedestrian's behavior and infrastructure [24], informing urban planning and road design decisions. Linear mixed statistical models have been employed to study the effects of distractions on children's behavior [25], providing valuable insights for designing safer school zones. Automated computer vision algorithms have analyzed the impact of cell phone usage on vulnerable road users' behavior at crosswalks [26], highlighting the dangers of distracted walking. Furthermore, ML techniques have been used to predict pedestrian behavior in urban scenarios and at signalized crosswalks [27], [28], enabling the development of more responsive and safer traffic systems.

In the critical area of crash prediction and detection, studies have proposed innovative frameworks based on bivariate extreme value theory, employing ML for crash classification [10], which offers more accurate risk assessments. Deep learning models have been used to identify high-risk locations using connected vehicle data [29], [30], leveraging the increasing connectivity of modern vehicles. Computer vision techniques combined with deep learning have been developed for crash detection in low-visibility conditions [31], addressing a significant challenge in road safety. Deep neural networks have been applied to predict highway crashes [32], [33], potentially allowing for preemptive safety measures. Additionally, natural language processing techniques have been used to detect road accidents from social networking data [34], demonstrating the potential of non-traditional data sources in enhancing road safety.

Academic research has demonstrated the significant impact of AI on various aspects of transportation safety. Studies have shown improvements in efficiency through advanced traffic flow prediction models, enhanced safety via driver behavior monitoring and crash prediction systems, and better data governance through the integration of big data analytics. User experience has been positively affected by AI applications in pedestrian safety, while system management has benefited from improved crash detection methods and the utilization of non-traditional data sources. These advancements have led to more accurate real-time predictions, reduced accidents caused by human error, more effective preventive measures, and faster emergency response times. However, challenges remain in terms of data quality, infrastructure integration, and privacy concerns, which future research will need to address to fully realize the potential of AI in transportation safety.

Complementing academic efforts, numerous projects funded by DOTs and other related agencies have focused on practical implementations of AI in safety systems. For example, the Mineta Transportation Institute, supported by the USDOT, developed an AI Pedestrian Traffic Safety System to address the critical issue of pedestrian fatalities in urban areas [35]. The AI Pedestrian Traffic Safety System project aims to enhance pedestrian and cyclist safety in urban areas, with a focus on Los Angeles. The system utilizes existing traffic cameras as input to monitor VRUs in real time. The technical approach employs a sophisticated series of AI and computer vision algorithms to process video feeds, enhance image quality, detect objects (specifically pedestrians and cyclists), and track their movements. The system leverages advanced AI methods for object detection, feature extraction, and real-time data processing. The output is highly accurate, real-time data on pedestrian and cyclist movements, which can be applied to dynamic traffic control and targeted safety interventions. During testing, the system demonstrated impressive performance, achieving over 98% accuracy in counting pedestrians. This technology addresses multiple aspects of transportation safety. It enables real-time monitoring of vulnerable road users, facilitates dynamic traffic control to prevent crashes, provides crucial data for targeted safety interventions, and supports urban planning and infrastructure improvements. The report highlights several potential benefits of the system. It is notably cost-effective as it utilizes existing camera infrastructure, making it highly scalable for covering large urban areas. The system also offers improved accuracy over previous automated systems and provides real-time data processing capabilities for immediate safety interventions. However, the report also acknowledges potential risks and challenges. These include issues with poor video quality due to low camera resolution, inadequate lighting, or adverse weather conditions. Suboptimal camera angles or locations and interference from shaking cameras or blocking objects are also noted as potential hurdles.

Researchers from C2SMART have proposed a Vehicle Overheight Warning System for Bridges [36]. The system's input consists of traffic images captured by long-range cameras capable of operating in various conditions, including day, night, and adverse weather. The technological approach involves using detection and instance segmentation techniques, specifically employing the YOLOv8 algorithm. The system's output is intended to be an early warning when an overheight vehicle is detected approaching a low-clearance bridge. This project primarily addresses the aspect of collision prevention in transportation safety, specifically targeting the reduction of bridge strikes by overheight vehicles. The report mentions several potential benefits, including significant cost savings from preventing bridge damage, enhanced safety for drivers and passengers, and improved traffic mobility. However, it also acknowledges some risks and challenges. These include further improving the height estimation precision, potential issues with false positives or negatives in vehicle detection, and the need for extensive testing in various real-world conditions. The report also highlights the importance of addressing technological challenges such as precise vanishing point estimation for different truck shapes and dealing with background noise and shadows in images.

The Road Ecology Center at the University of California, Davis, developed an automated system for analyzing and managing environmental data from camera traps [37]. The project's overall goal was to improve the efficiency of processing and analyzing images of wildlife near roadways to enhance highway safety and wildlife protection. The system takes in camera trap images as input and utilizes AI processes, particularly image analysis and ML techniques, to automatically detect and identify animals in the images. It also includes tools to determine if multiple images show the same animal or group of animals and a video tagging tool to analyze animal behavior. The outputs include sorted and processed images with species identification and behavioral analysis. This system supports transportation safety by helping monitor wildlife activity near roads, which can inform measures to reduce wildlife-vehicle collisions and improve highway design for both human and animal safety. The report mentions that automating these processes results in reduced costs for State Departments of Transportation while increasing environmental surveillance capabilities. However, the report does not specifically mention potential risks or provide exact cost figures for the system. The benefits highlighted include improved efficiency in environmental assessment and management related to wildlife-highway interactions.

The Mineta Transportation Institute at San José State University proposed a pedestrian detection and avoidance system aimed at reducing nighttime pedestrian fatalities involving motor vehicles [38]. The project's overall goal was to create a high-accuracy system for detecting pedestrians to prevent accidents. The system utilizes three kinds of sensors, including visual cameras, infrared cameras, and radars, combined with ML techniques. Specifically, deep convolutional neural networks (DCNNs) were employed to process data from the visual and infrared cameras, while the radar sensor provided range and motion information. The system outputs real-time alerts to drivers through a vibrating steering wheel and dashboard display when pedestrians are detected. This technology primarily addresses transportation safety in the areas of pedestrian detection and collision avoidance, with potential applications in autonomous vehicle automatic braking systems. The report mentions several benefits, including high detection accuracy (over 97% in both day and night conditions) and the ability to function in various lighting and weather conditions. Potential risks or limitations noted include degraded accuracy for detecting pedestrians at greater distances due to camera resolution constraints.

Moreover, Georgia DOT has funded a project for an AI-based system for automatically identifying traffic conflicts at signalized intersections using existing traffic monitoring cameras [39]. The project's primary goal was to create a system capable of identifying traffic conflicts, using existing traffic monitoring cameras. The system takes live video feeds from intersection cameras as input and employs deep learning techniques for vehicle detection. The system analyzes the extracted trajectories to identify potential conflicts and quantifies them using a novel "Conflict Gravity Model" that assesses both collision risk and potential severity. The system's output includes detailed conflict event data, such as vehicle speeds, angles, and computed risk metrics. This information can be used for various safety applications, including proactive crash prediction, intersection design evaluation, and real-time safety monitoring. The report highlights potential benefits of the system, such as its ability to provide a proactive approach to safety management, potentially reducing crashes before they occur. It could also evaluate the safety implications of emerging technologies like autonomous vehicles. However, the report also notes some risks and challenges, including computational resource requirements for real-time processing of multiple video streams and the need for further improvements in detection accuracy and robustness to minimize false detections. The researchers recommend future work to address these challenges and suggest exploring alternative camera setups to improve detection accuracy.

The Renaissance Computing Institute at the University of North Carolina and the North Carolina DOT have proposed an AI system for rural road monitors [40]. They aimed to enhance roadway safety, particularly in rural areas, by leveraging AI methodologies to evaluate rural roadside features. The system uses video data as input. The AI tool utilizes transfer learning, active learning, and a common feature extraction backbone approach to efficiently train and improve the models. The output includes accurate detection and classification of roadside features, which are then integrated into NCDOT's geographic information system (GIS) linear referencing system. The report highlights potential benefits such as improved assessment of roadside risks and more efficient prioritization of safety countermeasures. However, it also notes limitations, including the need for more precise localization of detected features and the challenge of obtaining sufficient labeled training data. The project team suggests future work to address these limitations, including combining AI with classical computer vision algorithms for 3D feature placement, employing self-supervised learning to reduce manual labeling requirements, and incorporating additional data streams like LIDAR for enhanced feature detection and ground topography analysis.

The University of Tennessee and the University of North Carolina developed a collaborative research project aimed at improving pedestrian safety at intersections through the application of AI and data analysis techniques [41]. The project's overall goal was to enhance driver-pedestrian interactions and reduce pedestrian fatalities at intersections. The research utilized various data sources, including traffic signal camera feeds, and crash databases. The project employed several AI and data analysis methods, including reinforcement learning algorithms for traffic signal optimization, unsupervised ML (K-means clustering) to identify extreme crash cases, and random forest models to classify pedestrian injury severity. The project's outputs included an AI-based decentralized algorithm for traffic flow optimization that prioritizes pedestrian safety, a systematic procedure to detect corner cases in fatal pedestrian-vehicle crashes, and insights into the determinants of nighttime pedestrian crash injury severity at intersections and non-intersections. These outputs contribute to multiple aspects of transportation safety, including crash prediction, injury severity analysis, and traffic signal optimization for pedestrian safety. The report highlights potential benefits such as improved pedestrian safety through optimized traffic signals, a better understanding of rare and extreme crash scenarios, and targeted interventions based on identified risk factors. However, it also notes potential risks, such as the challenge of balancing pedestrian safety with traffic efficiency and the need for careful implementation of AI-based systems in real-world traffic environments. The report emphasizes the importance of validating these approaches with real-life data and considering the ethical implications of AI-driven decision-making in traffic management.

Clemson University developed a cloud-based road hazard detection and warning system using smartphones [42]. The project's overall goal was to create a cost-effective and efficient method for identifying road hazards such as potholes, bumps, and obstacles in real-time. The system utilizes motion data collected from smartphone sensors mounted in vehicles, as well as simulated data from the BeamNG physics engine. The technical approach combines LSTM for hazard classification with cloud-based data fusion and k-means clustering for improved accuracy. The system outputs road hazard detections with location data, which are displayed on a web interface for authorities to monitor. This project contributes to transportation safety by enabling early detection and reporting of road hazards that could potentially cause accidents or vehicle damage. While the report does not explicitly discuss risks, it mentions potential benefits, including improved driving comfort, safety, and the ability to continuously monitor road conditions at a lower cost compared to traditional methods. The system's accuracy and reliability were demonstrated through various experiments, showing promise for real-world application in enhancing road safety and maintenance efforts.

The University of Utah has developed a framework for a monitoring tool that can help transportation professionals identify and respond to non-recurrent traffic events, such as crashes, on arterial roads [43]. The researchers used raw datasets from the UDOT, as well as crash data, to build a database of information about traffic patterns and crash events. They employed LSTM to create a monitoring tool that can not only record the results of traffic anomalies but also identify when road conditions are similar to those of past crashes, potentially enabling proactive response measures. The report suggests that this monitoring tool could be used to improve various aspects of transportation safety, such as travel time reliability, environmental outcomes, and user safety. While the tool itself is still in development, the researchers are working on making the database of information publicly available, which could benefit agencies and stakeholders with concerns about improving traffic operations and safety analyses. The report does not explicitly mention any potential risks associated with the development and deployment of this monitoring tool. However, it highlights the benefits of being able to identify and respond to non-recurrent traffic events, such as crashes, in a more timely and effective manner, which could lead to improved safety, efficiency, and environmental outcomes for the transportation network.

The Massachusetts DOT (MassDOT) commissioned a research project to develop an AI framework for detecting crosswalks across the state of Massachusetts [44]. The primary goal of this project was to create a comprehensive inventory of crosswalk locations, types, and categories (intersection, midblock, driveway) to support pedestrian safety initiatives and traffic planning. The researchers utilized annotated aerial imagery from 2019 and 2021 to train a deep learning model, specifically the DeepLabv3Plus architecture, to detect and classify crosswalks. The model was able to accurately identify continental (zebra) crosswalks, standard parallel line crosswalks, and solid/painted crosswalks, with an overall accuracy of over 99%. After the initial AI-based detection, the researchers implemented a post-processing framework to further refine the results, filtering out false positives and categorizing the crosswalks based on their location relative to the road network. The output of this project is a comprehensive GIS-based crosswalk inventory for the entire state of Massachusetts, which can be used to inform various transportation safety initiatives, such as maintenance, safety improvements, and risk modeling for pedestrian crashes. The report highlights the significant time and cost savings achieved by leveraging AI technology, compared to manual identification of crosswalks from aerial imagery. The report also discusses some potential risks and benefits of this approach. While the AI model demonstrated high accuracy, there were still some false positives that required manual validation. Additionally, the report suggests that incorporating techniques to account for wear and tear, as well as shifts in crosswalk locations between years, could further improve the robustness of the crosswalk inventory.

The University of Tennessee and the University of North Carolina developed an AI-based framework to monitor the drivers, cars, and roadways [45]. The overall goal of the project is to quantify the risks associated with driver impairment and distraction in terms of safety-critical events. The team utilized naturalistic driving data to analyze the relationship between driver impairment and crashes and near-crashes. They applied various statistical and ML techniques, such as binary logistic regression, 1D-CNN, LSTM, and 1DCNN-LSTM models, to predict the occurrence of safety-critical scenarios. The report acknowledges the limitations of the study, such as the lack of detailed roadway information and the inability to analyze lane-keeping performance due to data constraints. However, the project demonstrates the potential of leveraging multi-modal sensor data and advanced AI techniques to enhance transportation safety through the early detection of driver impairment and distraction.

The Collaborative Sciences Center for Road Safety developed a study to evaluate vehicle-to-pedestrian safety [46]. The overall goal of this project was to examine how to use a cell phone to prevent crashes. The researchers used a remotely controlled alerting system on the smartphone to provide early, just-in-time, and late alerts to the participants, with varying degrees of reliability (80%, 90%, and 100%). The study employed a decision tree model to analyze the collected data and identify the factors that contributed to safe versus risky crossings. The study identified potential risks and benefits associated with the use of technological interventions, such as smartphone alerts, for promoting pedestrian safety. While the alerts were not as effective as expected, the researchers suggest that further research, including larger datasets and investigations into the influence of cultural and personality factors, could help elucidate design criteria for more effective safety solutions.

The University of Massachusetts Amherst developed a new video analysis model to quantify the impacts of situational visual clutter on driving performance using driving simulation data and eye-tracking information [47]. This project has the potential to support transportation safety research, particularly in areas such as crash prediction and driver behavior analysis, by leveraging existing driving simulation data and quantifying the impacts of situational visual clutter. The report mentions the potential risks and benefits of the developed methodology. The researchers note that the image segmentation and object detection accuracy were constrained by the available dataset and that the methodology could be further improved by evaluating other deep learning and image processing approaches, investigating the impact of uncalibrated eye-tracking data, and incorporating vehicle status data to reveal more insights on how situational visual clutters affect driving performance.

The University of Idaho developed a project to explore the capabilities of computer vision for pedestrian safety analysis [48]. The goal was to use computer vision to track the movement of cars, bikes, and pedestrians, as this technology can provide superior information about speed, trajectory, and count data for various transportation modes. The report highlights the potential benefits of using computer vision for transportation safety applications, such as crash prediction and pedestrian safety analysis. However, it also mentions potential risks, such as the need for a deeper understanding of the YOLO V8 model's limitations, particularly in accurately estimating pedestrian walking speeds due to issues with object occlusion and random object identification.

Nevada Department of Transportation (NDOT), in collaboration with the Nevada Department of Public Safety (DPS) Highway Patrol Division, the Regional Transportation Commission of Southern Nevada (RTC), and Waycare, developed an AI-based traffic management system aimed at reducing traffic incidents in Southern Nevada [49]. The project's primary goal was to curb traffic incidents on key corridors of I-15 and US-95. The system utilized AI algorithms and predictive analytics to identify high-risk corridors and times for potential crashes, using existing local data sets as input. The technology enabled strategic police positioning and dynamic messaging signs to proactively address safety concerns. This approach targeted multiple aspects of transportation safety, including crash prediction, speed reduction, and proactive incident response. The project resulted in an 18% reduction in primary crashes and a 43% reduction in speeding drivers along the focus corridors. The report highlighted significant benefits, including substantial economic savings totaling $3,000,993 due to prevented property damage, medical costs, productivity loss from travel delays, and other agency-incurred expenses related to road crashes. The cost-benefit analysis showed a 16x return on the initial investment. While specific risks were not explicitly mentioned in the provided excerpt, the project demonstrated the potential of AI and interagency collaboration in enhancing road safety. The success of this program suggests it could serve as a blueprint for scalable and effective future strategies combining technology and interagency cooperation in traffic management and safety.

The Mineta Transportation Institute at San José State University has developed an AI-based system for vulnerable road users [50]. The developed system is intended to be used for transportation safety, particularly in monitoring busy intersections prone to traffic accidents involving pedestrians and cyclists. By accurately detecting, tracking, and counting these vulnerable road users, transportation agencies can better manage traffic flow and implement safety measures to protect them. The report mentions several potential challenges and risks associated with using this system, such as poor video quality, lighting conditions, camera angles, and vibrations. However, the system has demonstrated high accuracy and effectiveness in real-world tests, with an average hourly error of only 4.1% in pedestrian counting. This suggests that the benefits of improved pedestrian and cyclist safety outweigh the potential risks, making this a valuable tool for transportation agencies to enhance road safety.

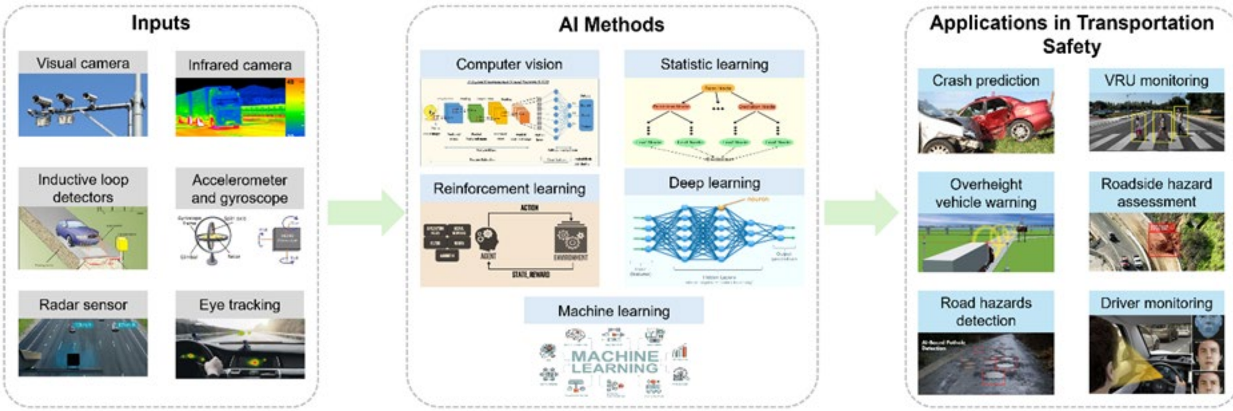


Figure A3 AI-Driven Methods and Applications for Enhancing Transportation Safety.

Figure A3 provides a structured overview of transportation safety projects, illustrating the relationship between various inputs, methods, and applications. This visual representation, combined with the previously discussed works and projects, offers a comprehensive look at the current state of transportation safety innovation. Inputs for these projects come from a diverse range of sources. Visual cameras and infrared cameras provide rich visual data, while inductive loop detectors offer traffic flow information. Smartphone sensors, including accelerometers and gyroscopes, contribute motion and orientation data. Radar sensors add another layer of detection capability, particularly useful for measuring speeds and distances. Eye tracking technology introduces a human factors element, allowing for the analysis of driver attention and behavior. These inputs feed into several advanced computational methods. Computer vision stands out as a primary technique, capable of processing visual data to detect objects, analyze scenes, and track movement. Reinforcement learning, statistical learning, deep learning, and ML algorithms form the backbone of the analytical capabilities, allowing systems to learn from data, make predictions, and improve over time. The applications of these technologies are varied and impactful, including crash prediction, VRU monitoring, overheight vehicle warning, roadside hazard assessment, road hazard detection, and driver monitoring.

The above-mentioned projects and works demonstrate a wide range of innovative approaches using AI, computer vision, and data analytics. These technologies offer significant potential benefits for improving road safety, traffic management, and infrastructure maintenance. The key benefits of these projects are multifaceted. They include enhanced detection and analysis of safety hazards, such as pedestrians, vehicles, and road conditions, as well as improved real-time data processing for immediate safety interventions. Many of the projects demonstrate cost-effectiveness through the utilization of existing infrastructure, which could lead to significant reductions in crashes and associated costs. The technologies also offer the potential for a better understanding of rare and extreme crash scenarios, more efficient prioritization of safety countermeasures, and improved assessment of roadside risks.

However, implementing AI in transportation safety still faces challenges. For instance, poor video quality, lighting conditions, or adverse weather are common concerns. There's also the potential for false positives or negatives in object detection, which necessitates extensive real-world testing and validation. Many of the projects require significant computational resources for real-time processing, which can be a challenge for widespread implementation. Data privacy and ethical concerns related to AI-driven decision-making are important considerations, as is the challenge of balancing safety improvements with traffic efficiency. Several projects noted limitations in available datasets for training AI models, highlighting the need for more comprehensive data collection efforts. Finally, the careful implementation and integration of these new systems with existing infrastructure remains a crucial challenge.

Transportation Operations

Recent years have witnessed a significant surge in academic research focusing on AI applications in transportation operations. This research trend reflects the growing recognition of AI's potential to revolutionize traffic management and improve overall transportation efficiency. A comprehensive survey by Guo et al. [51] laid the groundwork for understanding AI's role in urban traffic signal control with connected and automated vehicles (CAVs). Their work highlighted the paradigm shift from traditional traffic control methods to AI-driven approaches capable of handling the complexities of mixed traffic scenarios. Various AI techniques, including reinforcement learning and deep neural networks, being used to optimize signal timing and vehicle trajectories in real-time were highlighted in this paper. In the realm of intersection management, Yu et al. [52] proposed an integrated optimization framework for traffic signals and vehicle trajectories at isolated urban intersections. Their approach demonstrated the potential of AI in coordinating CAVs and traditional vehicles to improve traffic efficiency. Building on this, Yu et al. [53] developed a cooperative trajectory optimization method for CAVs. Their approach utilized AI algorithms to optimize vehicle trajectories across multiple intersections, underscoring the potential of AI in managing traffic at a broader scale.

Feng et al. [54] introduced a spatiotemporal intersection control method specifically designed for CAV environments. Their AI-driven approach optimized both spatial and temporal aspects of traffic flow. This work highlighted the capacity of AI to make real-time decisions that significantly enhance traffic operations. To address the challenge of low CAV penetration rates, Ma et al. [55] developed an innovative signal timing optimization method using aggregated vehicle trajectory data. Their research showed that AI could effectively optimize traffic signals even with low CAV penetration rates, demonstrating its potential in the transitional period toward fully automated transportation systems. Wang et al. [56] explored adaptive and multi-path progression signal control in connected vehicle environments. Their AI-based approach dynamically adjusted signal timings based on real-time data from connected vehicles, achieving a reduction in average travel time along arterial roads. This research illustrated AI's capability to adapt to changing traffic conditions in real-time.

At the network level, Yan et al. [57] proposed a multiband signal coordination scheme utilizing vehicle trajectory data. This approach employed a heuristic algorithm inspired by evolutionary computation. Their AI-driven method optimized traffic flow across entire urban networks, resulting in an increase in average speed and a reduction in stop times compared to traditional coordination methods. Wang et al. [58] investigated cooperative eco-driving strategies at signalized intersections. They used reinforcement learning algorithms to optimize vehicle trajectories for reduced fuel consumption while maintaining traffic efficiency, showcasing AI's potential in addressing both operational and environmental concerns. Guo and Ma [59] introduced a two-stage learning and control framework for joint optimization of intersection signals and CAV trajectories. Their approach combined deep learning for traffic pattern recognition and reinforcement learning for signal control, demonstrating how different AI techniques can be integrated for comprehensive traffic management. Li et al. [60] proposed a novel approach using AI-controlled CAVs as mobile actuators to manage mixed traffic flow at intersections. They employed a multi-agent reinforcement learning algorithm where each CAV acts as an agent, learning to optimize its trajectory to influence surrounding traffic positively. Chen et al. [61] developed an AI-driven cooperative control strategy for mixed platoons at signalized intersections. They used a combination of deep neural networks for platoon state prediction and reinforcement learning for joint optimization of platoon formation and signal timing. Jiang et al. [62] introduced a multi-agent reinforcement learning framework for network-wide traffic signal control in mixed traffic environments. Each intersection in their system was controlled by an individual reinforcement learning agent, with a novel cooperative learning mechanism allowing agents to share experiences and improve collectively.

The integration of AI into transportation operations systems has marked a significant advancement in traffic management across the United States. The Washington State DOT (WSDOT) developed a fuzzy logic ramp metering algorithm for freeway operations in the greater Seattle area [63]. The project aimed to improve freeway efficiency by optimizing ramp metering control. The system uses real-time traffic data from loop detectors as input. The algorithm employs fuzzy logic control techniques to balance multiple, often conflicting objectives. The output is optimized metering rates for each on-ramp. The system was implemented on 126 ramp meters across the Seattle area. The report highlights several benefits, including improved mainline efficiency, reduced congestion, and easier maintenance of the ramp metering system. It also notes the algorithm's ability to handle a wide range of traffic conditions without constant adjustment.

Potential risks include the need for proper detector placement and the challenge of balancing multiple objectives in heavily congested areas. The project required significant investment in software development, with over 90% of the budget allocated to this aspect. While specific cost figures are not provided, the report emphasizes the importance of adequate funding for software development, testing, and integration in complex transportation management systems.

Building on this success, the California DOT has integrated similar AI technology into its active traffic management system along the critical I-80 corridor [5]. The fuzzy logic-based ramp metering system simplifies the configuration of the algorithms by using more generalized and linguistic descriptions of traffic conditions, such as "heavy traffic" or "light traffic," rather than relying on detailed and difficult-to-maintain models. California DOT is now considering the statewide standardization of the fuzzy logic-based ramp metering method, but it is not yet mandated across all districts. The Texas A&M Transportation Institute developed a project for alleviating freeway congestion [64]. The report mentions potential risks and benefits of the project, such as the ability to leverage big data and AI to enhance transportation operations, as well as challenges related to data governance and resource limitations. The project had a budget of $297,204 over two years, and the value of the research analysis estimated an annual benefit of $698,850 with a cost-benefit ratio of 16.30.

Taking AI integration a step further, the Delaware DOT (DelDOT) has implemented an advanced AI-based Integrated Transportation Management System (AI-ITMS) [65]. This project aims to leverage AI and ML technologies to enhance transportation management and improve road safety across the state. The system integrates various data sources, including traffic sensors, connected vehicles, and machine vision cameras, to provide comprehensive real-time insights into traffic conditions. The AI-ITMS employs several advanced technologies, including data fusion, short-term traffic flow prediction, proactive incident management, machine vision for traffic monitoring, and adaptive signal timing. These AI methods are used to analyze the input data and generate actionable insights for transportation operations. The system's output includes traffic flow predictions, incident detection and response recommendations, automated traffic signal performance measures, and connected vehicle data integration. While the report does not explicitly mention specific risks or costs associated with the project, it highlights several potential benefits. These include improved traffic flow, enhanced safety through proactive incident management, more efficient signal timing, and better integration of connected and automated vehicles. The system is designed to continuously learn and adapt, potentially leading to a more intelligent and responsive statewide transportation management system over time. The report also emphasizes the need for staff with appropriate knowledge and skills to support and maintain this advanced system, suggesting a potential area of investment for the department.

The CCAT at the University of Michigan developed an end-to-end framework for analyzing transportation network equilibrium [66]. The overall goal of this project is to learn the supply-side and demand-side components of transportation networks directly from traffic data, using computational graphs and neural networks to parameterize unknown elements. The input to the framework includes multi-day traffic state observations, such as link flows and travel times, as well as various contextual features like weather and road network attributes. The researchers proposed a novel neural network architecture that guarantees the existence of equilibrium states and allows for future scenario planning. The output of this framework is a set of learned parameters for the supply-side link performance functions and demand-side travel choice models, as well as the estimated equilibrium traffic states. This can be used to support transportation operations in various applications, such as planning network improvements, evaluating the impacts of policy changes, and predicting traffic conditions. The potential risks and benefits of this approach, as well as the estimated development costs, are not explicitly discussed in the report.

FHWA developed an AI-based incident detection framework to improve traffic management center (TMC) operations [67]. The project aimed to leverage large-scale sensor data and advanced learning algorithms to enhance the performance of incident detection compared to conventional approaches. The input data for the framework included traffic flow, speed, and occupancy measurements from loop detectors along the highway. The methodology involved an AI-based approach that combined a tuned neural network model with a memory unit to store and learn from historical traffic profiles and incident occurrences. The report discussed potential future work, such as validating the approach with real-world data, incorporating additional input data sources (e.g., weather, time of day), and exploring more advanced deep learning algorithms. While the simulation-based evaluation indicated promising results, the report did not provide specific cost estimates for implementing the AI-based framework. The key potential benefit is improved incident detection performance, leading to more efficient transportation operations and increased safety for both motorists and responders.

The University of North Carolina developed a project to explore the use of deep reinforcement learning to optimize traffic signal control in transportation networks [68]. The results demonstrated that the Deep Q-Learning (DQN) outperformed the non-learning controllers in terms of measures like average travel time, queue length, and vehicle delays, even when applied to lower traffic demand situations or networks without incidents. The report highlighted the importance of thorough hyperparameter tuning, which was crucial for achieving optimal performance of the DQN model. The authors also noted that the DQN's decision-making process can be opaque, making it challenging to explain why the model performs better than traditional approaches. The University of Michigan developed a real-time distributed optimization system for traffic signal timing optimization in urban traffic networks [69]. The proposed techniques have the potential to improve transportation network operations by optimizing traffic signal timing, increasing throughput, and reducing travel delay. The report highlights the benefits of considering uncertainties and coordinating intersections, as well as the advantages of the decentralized, end-to-end control policies for real-world implementation. While the report does not provide specific cost estimates, it suggests that the advanced technologies in smart transportation, such as distributed micro-computers and vehicle-to-infrastructure communication, can enable the practical deployment of the proposed approaches. The report also discusses potential risks, such as the need for accurate real-time traffic state estimation and the challenges in scaling up the reinforcement learning algorithms for large-scale networks.

The Illinois Center for Transportation developed a research project focused on using AI and data-driven approaches to optimize truck platooning and its impact on autonomous freight delivery [70]. The researchers developed data-driven surrogate models, including generalized additive models and artificial neural networks, to efficiently predict the drag force of the platoons without relying on computationally expensive computational fluid dynamics simulations. Using the surrogate models, the researchers conducted a case study on a 160 km corridor in Illinois to analyze the fuel consumption and delivery costs of a three-truck platoon compared to conventional truck delivery. The results showed that the truck platoon could achieve up to 10% fuel savings depending on the headway between trucks, and the total delivery cost could be reduced by 30% through automation and reduced labor requirements. The report highlights the potential benefits of truck platooning in improving energy efficiency and reducing operational costs in the freight industry. However, it also notes the need to carefully consider factors like wind conditions and truck configurations to optimize the performance of truck platoons. The researchers demonstrate the value of data-driven, AI-based approaches in enabling real-time adjustments to truck platoon formations to maximize fuel savings and delivery efficiency.

The University of Utah developed a comprehensive connected vehicle (CV) based traffic signal control system for urban arterials [71]. The project's overall goal was to establish a real-time adaptive system to support CV-based traffic signal control functions while accommodating a large number of connected vehicles. The system takes inputs such as CV trajectory data, signal phase and timing information, and roadside sensor data. It employs various AI and optimization methods, including dynamic programming, integer optimization, and adaptive control algorithms. The outputs include optimized signal timings, vehicle advisory speeds, and traffic progression plans. The report discusses several potential benefits, including improved arterial mobility, enhanced intersection safety, reduced traffic delays, and better accommodation of transit vehicles. It also highlights the system's capability to handle mixed traffic patterns of connected and human-driven vehicles. While specific costs are not mentioned, the report indicates that the proposed system can utilize existing infrastructure more efficiently compared to traditional methods. Potential risks are not explicitly discussed in the provided summary, though challenges such as low CV penetration rates and the need for robust communication networks are mentioned. The report emphasizes the system's ability to improve both safety and operational efficiency, suggesting that it aims to mitigate risks associated with traditional traffic control systems.

The Purdue University CCAT developed a two-part project to address urban traffic congestion using emerging technologies [72]. The report did not explicitly mention any potential risks or costs associated with the proposed systems. However, the focus on leveraging emerging technologies like connectivity, automation, and AI-based control algorithms suggests that there may be challenges related to technology adoption, regulatory frameworks, and infrastructure investment that would need to be addressed. Carnegie Mellon University and the University of Washington have developed an AI-based traffic management system [73]. The system utilizes various data sources, including probe vehicle speed, weather data, GPS-based smartphone applications, incident feeds from state DOTs, and traffic counts, which are fused and analyzed through advanced AI and ML techniques. The AI models developed include unsupervised early anomaly subgraph detection, origin-destination estimation, low-rank surrogate models, intervention-aware traffic prediction, and reinforcement learning algorithms for optimal proactive traffic management decisions. The researchers evaluated the prototype system through simulation and case studies, deploying it on the I-70 corridor network in Maryland and the regional network in Cranberry Township, Pennsylvania. The system demonstrated the ability to predict non-recurring traffic events up to 30 minutes in advance and recommend proactive operational management strategies to mitigate the impact on mobility, safety, and energy use. While the report does not explicitly mention the potential risks or costs associated with the project, the development of this advanced traffic management system has the promise to significantly improve the efficiency, safety, and sustainability of transportation operations in large-scale networks.

FHWA awarded a $1 million grant to the Missouri DOT for its Predictive Layered Operation Initiative (PLOI) on I-270 [74]. The project's overall goal is to improve response and operations on I-270 through the deployment of a predictive analytics platform. The system uses complex algorithms that analyze traffic, weather, and incident data as inputs. It employs AI and predictive modeling techniques to determine the likelihood of crashes, identify response times, and assess the potential impacts of various factors on traffic conditions. The project is primarily focused on improving traffic incident management and winter maintenance operations. Additionally, it aims to enhance public safety by predicting crash risks associated with events like major sporting activities. While the report does not explicitly mention potential risks, it highlights the benefits of improving safety and efficiency on roads through advanced technology deployment. The cost of this specific project is stated as $1 million, which is part of a larger $43.3 million ATCMTD program funding ten innovative transportation projects across the country.

The Michigan Department of Transportation has developed the Intelligent Woodward Corridor Project [75]. The project's overall goal is to improve mobility and safety along Detroit's Woodward Avenue corridor through an intelligent transportation network. Inputs include real-time traffic data, pedestrian movement information, and vehicle communications. The technical approach incorporates four main technologies: pedestrian detection and alerts, traffic signal prioritization, vehicle-to-vehicle and vehicle-to-infrastructure communications, and advanced data analytics. While specific AI methods aren't detailed, the project mentions using artificial intelligence, likely for traffic prediction and management. Outputs are expected to include real-time traveler information and optimized traffic flow. The project addresses multiple aspects of transportation operations, including traffic signal optimization, pedestrian safety enhancement, and emergency vehicle prioritization. Potential benefits include reduced congestion and improved safety for both drivers and pedestrians, though specific risks are not mentioned in the report.

The Tennessee DOT (TDOT) developed an AI-based Decision Support System (AI-DSS) to help efficiently manage their diverse Intelligent Transportation Systems (ITS) device inventory [76]. The project's overall goal was to leverage AI to improve highway performance and safety and reduce congestion along the I-24 SMART Corridor. The system integrates various ITS components, such as lane control signs, variable speed limits, vehicle detectors, cameras, and traffic signals, across multiple agencies and municipalities and manages them as a single integrated system supported by AI. By using AI to quickly process and understand the data, the AI-DSS can make intelligent decisions instead of relying on traditional corridor-specific traffic models. The project aims to reduce the cost and time it takes to deploy decision support systems across Tennessee, serving as a benchmark for what's possible in the transportation sector across the country. The report mentions that by leveraging AI, the system has achieved a 12% reduction in fatal/serious crashes and a 6% improvement in vehicle flow, demonstrating the potential benefits of this innovative solution. While the report does not explicitly mention any risks or the overall project cost, it highlights the groundbreaking opportunity for TDOT to increase safety on the most traveled roadway in the state, showcasing the transformative power of AI in transportation operations.

Figure A4 illustrates the interconnected nature of modern transportation operations, showing how various inputs, methods, and applications work together to create intelligent transportation systems. Inputs range from traditional sources like inductive loop detectors and road weather data to more advanced ones such as visual camera feeds, social media data, and probe vehicle data. These diverse data sources feed into a variety of analytical methods, including computer vision, natural language processing, statistical learning, deep learning, ML, and reinforcement learning. These advanced analytical methods are then applied to a wide array of transportation management applications. These applications include ramp metering, traffic flow prediction, traffic signal timing optimization, variable speed limit systems, traffic incident detection, and vehicle platooning.

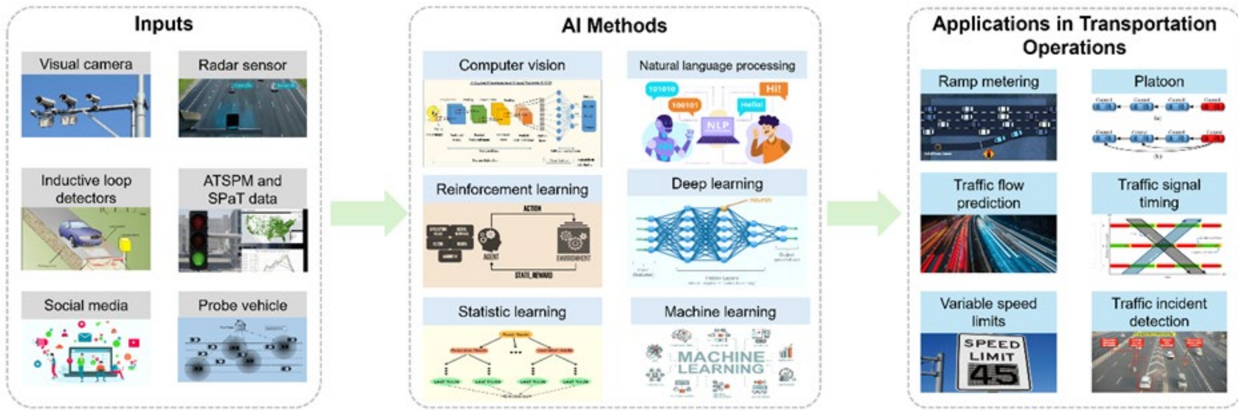


Figure A4 AI-Driven Methods and Applications for Enhancing Transportation Operations.

In summary, AI has demonstrated significant benefits in improving transportation operations. Key advantages include enhanced traffic flow, reduced congestion, improved safety, and increased energy efficiency. For instance, some projects reported up to a 12% reduction in fatal/serious crashes and a 6% improvement in traffic flow. The implementation of AI has shown promise in optimizing traffic signal timing, predicting non-recurring traffic events, and enabling proactive management strategies. Additionally, innovations like truck platooning have demonstrated potential fuel savings of up to 10% and reduced delivery costs by 30%. However, these projects also face certain risks and challenges. These include the need for accurate real-time data collection, proper sensor placement, and the complexity of balancing multiple objectives in heavily congested areas. The opaque nature of some AI decision-making processes poses challenges in explaining system behaviors. Furthermore, the successful implementation of these advanced systems requires staff with specialized knowledge and skills, highlighting the importance of workforce development. Regarding costs, the projects vary widely in their financial requirements. While some reports did not provide specific figures, others mentioned budgets ranging from approximately $300,000 for a two-year research project to $1 million for a larger-scale implementation. It is worth noting that a significant portion of project budgets (in one case, over 90%) is often allocated to software development, testing, and integration. Despite the substantial initial investments, many projects demonstrated favorable cost-benefit ratios, with one study estimating an annual benefit of nearly $700,000 against its costs.

Digital Twins

FHWA’s EAR Program is sponsoring researchers at Texas A&M Transportation Institute to develop a novel framework for traffic safety analysis called Digital Twin-Enabled Extended Active Safety Analysis for Mixed Traffic [77]. The project's overall goal is to build a predictive, extended, active safety approach for mixed traffic of human-driven vehicles and CAVs through digital twin technology. The inputs include static data on road geometries and ambient road environments, as well as dynamic data on high-resolution vehicular trajectories under different traffic conditions collected using portable sensors, CAVs, and drones. The project utilizes AI methods such as diffusion neural networks for data fusion and predictive algorithms for vehicle motion and trajectory. The output is an integrated system that enables three-dimensional active safety analysis, interactive multiple-vehicle motion prediction, and predictive safety analysis. This digital twin approach addresses the shortcomings of traditional surrogate safety measures (SSM) and enhances the application of digital twins in traffic safety analysis and simulation. The report mentions the potential benefits of achieving FHWA's goal of zero traffic fatalities but does not explicitly discuss the risks or costs associated with the project.

The University of South Carolina, in collaboration with Benedict College, developed a Digital Twin (DT) approach to evaluate load of precast reinforced flat slab bridges in rural South Carolina [78]. The input data for the DT model included results from full-scale laboratory testing of a bridge slab, finite element modeling calibrated with the experimental study, strain and displacement measurements, and acoustic emission data. The project employed an Artificial Neural Network (ANN) to classify autoencoder (AE) data and identify load steps. The output of the DT approach was an increased load rating factor compared to traditional methods. The DT approach was used for structural health monitoring and assessment of bridges, as well as for predicting the load-carrying capacity of an as-built bridge. The report mentioned that the DT procedure would benefit from additional data gathered both during testing and in the field. One potential risk identified was the variability associated with material properties found throughout the state, which should be incorporated into future studies. The benefits of this project include reduced costs on bridge maintenance and improved mobility. The report did not provide specific information on the project's cost.

The University of Texas developed a DT project to create DT systems for infrastructure [79]. The project used various inputs, including freely available data, open-source software, and reality capture techniques such as LiDAR scans. The team employed AI methods like object detection and tracking algorithms (YOLO and DeepSORT) for real-time vehicle detection and counting. The project outputs include a digital model of the UTEP campus, including the road transportation network, for visualization and simulation. These outputs were used for various aspects of digital twins. The report mentions the potential benefits of DT technologies, including improved planning, construction, and communication with stakeholders through immersive experiences. However, the report also highlights limitations and risks. The project faced challenges in obtaining detailed drawings or Building Information Modeling (BIM) models of campus buildings and delays in sensor installation due to bureaucratic procedures. The report does not explicitly mention the cost of the project.

Carnegie Mellon University developed a digital twin system for emergency traffic management [80]. The input data includes 3D scanning of real-world scenes, ambulance routing sample data, and sensor data from IMUs. The project utilizes various AI methods, such as sensor fusion, gait classification, and gesture tracking. These digital twins are used for training first responders, recovery planning, forensics, and providing situational awareness from multiple perspectives. The report mentions several potential benefits of the system, such as improving day-to-day operations and professional training for future transportation systems, benefiting governmental agencies, and the possibility of launching a startup to commercialize the technology. The project also had educational impacts, with the team launching a graduate course on drone information systems and training numerous students. However, the report does not explicitly mention any risks or costs associated with the project.

The University of Arkansas developed an AI-based DT for multimodal transportation systems [81]. Rutgers University developed the Mobi-Twin platform, a digital twin platform for smart mobility systems using high-resolution 3D data [82]. The platform takes in raw field video and point cloud data from roadside LiDAR and computer vision sensors as input. It employs various AI methods for background subtraction and multi-object tracking and detection. The output consists of vehicle and pedestrian trajectories, queue length estimation, signal performance measurements, and surrogate safety measures. The Mobi-Twin platform contributes to several aspects of digital twins, such as sensing and data acquisition, modeling and simulation, visualization, and application testing. The report does not explicitly mention any potential risks or costs associated with the project. However, it highlights the benefits include improved safety, and the potential to upgrade legacy detection systems at signalized intersections using LiDAR technology.

Carnegie Mellon University developed a Digital Twin for Driving project aimed at enhancing urban planning and traffic management through advanced simulation technologies [83]. The project's primary goal was to create a drivable digital twin of Philadelphia's Roosevelt Boulevard, integrating geospatial imagery with data from Google Maps and OpenStreetMap. The researchers utilized tools like CityEngine and RoadRunner to construct detailed, editable 3D urban scenes and implemented a dynamic traffic flow model within the Unity driving simulator. The project's input consisted of high-resolution tile maps, building outlines, and traffic data from the Next Generation Simulation (NGSIM) dataset. The team employed various AI and data analysis techniques, including image processing, 3D modeling, and statistical analysis of traffic patterns. They developed a novel traffic flow model using Gaussian distributions and probabilistic methods to simulate realistic vehicle behaviors. The output of this project was a comprehensive digital twin that could rapidly simulate and visualize changes to urban infrastructure, such as the addition of a bus lane. This digital twin addresses several aspects of urban digital twins, including infrastructure modeling, traffic simulation, and scenario testing for urban planning decisions. The report highlights potential benefits such as improved urban planning, enhanced traffic safety, and more efficient decision-making in infrastructure modifications. It also mentions limitations, including the reliance on available geospatial and traffic flow data and the computational demands of high-fidelity simulations. The researchers suggest that future work should focus on integrating real-time data feeds, developing more sophisticated traffic models, and incorporating multi-modal transportation systems. While the report does not explicitly mention specific costs associated with the project, it does acknowledge that the research was funded in part by a grant from Safety21, a University Transportation Center at Carnegie Mellon University, through the University of Pennsylvania, with support from the US Department of Transportation.

Rutgers University developed an advanced flood preparedness system that integrates remote sensing data, digital twin models, web technologies, and flood simulations [84]. The system uses high-resolution 3D mapping data collected by mobile LiDAR technology as input to create digital twins of coastal communities, such as Manville Township in New Jersey. It also incorporates calibrated hydrodynamic models to simulate flood conditions. The output of the system includes flood impact assessments for buildings and accessibility to emergency services, which are visualized through a web-based flood information dashboard. The digital twin models and flood simulations are used for various aspects, including infrastructure modeling, flood impact analysis, and decision support for flood mitigation strategies. The report does not explicitly mention the project's cost or specific potential risks and benefits. However, it concludes that the developed tools provide powerful means for community stakeholders to improve their resilience to flood events, suggesting potential benefits in enhancing flood preparedness and mitigating the impact of coastal storms on transportation infrastructure. A pilot digital twin framework for open-deck rail bridges was also developed by Rutgers [85]. The project's overall goal is to expedite sleeper assessment, outage times, and replacement procedures for open-deck bridges using modern technologies such as unmanned aerial vehicles (UAVs) and AI. The input for this system is UAV-based 3D scans of the bridge. The output is a digital representation of the bridge with identified positions and alignments of sleepers and tracks, which can be used for the inspection and maintenance aspects of digital twins. The report mentions that the potential benefits of this approach include improved bridge deck monitoring and cost savings in maintenance procedures. However, the report does not explicitly state the specific costs or risks associated with the project.

The Minnesota DOT and Collins Engineers, Inc. explored DT to reconstruct as-built data for MnDOT's building sites and buildings [86]. The collected data was processed into digital twins, including 3D reality models, 2D orthomosaics, and 2D ortho planes. Various software packages like Contextcapture, Pix4D, GeoSLAM, and Matterport were used for data processing. The digital twins were shared via cloud platforms, allowing easy access and utilization by team members. The project also explored the use of virtual reality and mixed reality for consuming the digital twin data. The benefits of this project consist of reduced costs, enhanced data sharing capabilities and safety. Digital twins provide team members with a photographic memory of the site, the ability to evaluate changes over time, and access to hard-to-reach areas. The upfront equipment costs for commercial setups ranged from $18,000 to $35,000. However, the technology can significantly reduce the need for site visits, leading to substantial cost savings. The report estimates that the cost of data collection and processing for one place is around $4,869. While the report does not explicitly mention risks, it emphasizes the potential for reduced risks and improved decision-making due to the availability of comprehensive and easily accessible data.

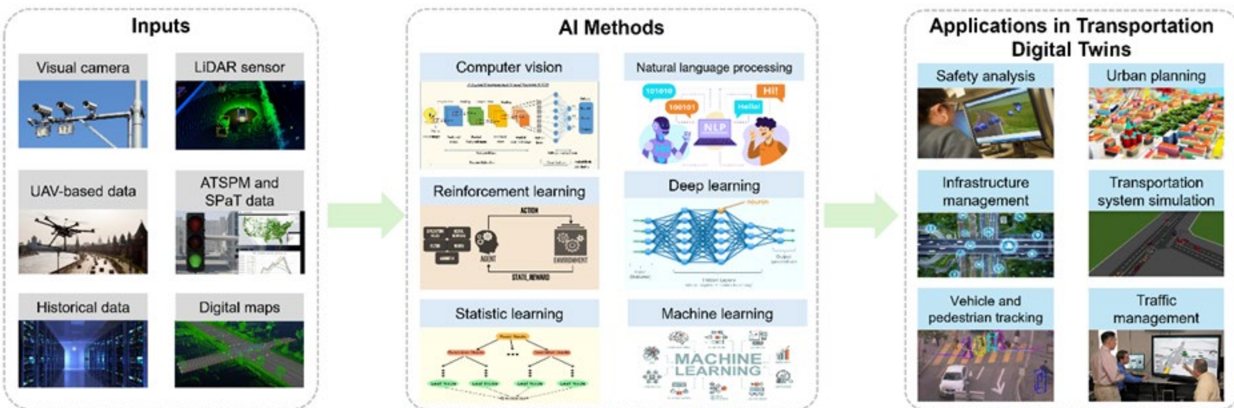


Figure A5 AI-Driven Methods and Applications for Digital Twins in Transportation.

Digital Twin technologies (Figure A5) offer numerous benefits across different applications. In traffic safety analysis, DTs address shortcomings of traditional surrogate safety measures and enhance simulation capabilities. For bridge monitoring, DTs enable improved structural health assessment and load-carrying capacity prediction, potentially leading to cost savings through reduced bridge replacements and increased mobility. In urban planning and construction, DTs provide immersive experiences that improve communication with stakeholders. For transportation systems, DTs can enhance day-to-day operations and professional training. In traffic safety applications, DTs allow for accurate analysis of near-miss conditions and identification of safety issues. For waterway systems, DTs contribute to improved operational efficiency and reduced transportation delays.

While the reports generally focus on benefits, some risks and challenges are mentioned. These include the variability of material properties in bridge studies, limitations in data availability and scale of implementation for urban DTs, and bureaucratic delays in sensor installation. The reports also highlight the need for additional data gathering to improve DT procedures. Regarding costs, specific figures are not always provided. However, as previously mentioned, one report mentions that commercial setups for DT workflows can cost between $18,000 and $35,000, with data collection and processing for a single site estimated at around $4,869. Despite these upfront costs, the reports suggest that DT technologies can lead to significant long-term cost savings through reduced site visits, improved maintenance procedures, and enhanced decision-making capabilities.

Autonomous Vehicles

Purdue University's CCAT developed an AI-based and control-based system for safe and efficient operations of CAVs [87]. The overall goal of the project was to enhance the safety and mobility of CAVs by integrating short-range sensor information and long-range connectivity information. The project utilized DRL techniques to fuse the spatially-weighted information from the CAV's local environment as well as the downstream environment obtained through V2V connectivity. This allowed the CAV to construct a comprehensive understanding of its surroundings and make informed, proactive driving decisions, particularly for lane-changing maneuvers. The researchers also investigated the critical connectivity range required for optimal CAV performance under different traffic density scenarios. The proposed framework was tested and evaluated against baseline models, demonstrating significant improvements in safety and efficiency. The report highlighted the potential benefits of the developed system, including reduced crashes, improved travel time, and lower operating costs. However, it also acknowledged potential limitations, such as the need to address domain adaptation, stability, and transparency issues inherent in reinforcement learning algorithms. The report did not provide specific cost estimates for implementing the system.

The University of Maryland developed a project to understand the impacts of AVs on traffic under different AV behaviors, penetration rates, and volume levels [88]. The aim was to provide highway agencies with guidelines on how to effectively use AVs and alleviate congestion. The researchers modified the model parameters of the AVs to reflect various aggressive, calibrated, and moderate driving settings. They then conducted extensive simulation experiments to analyze the measures of effectiveness. The report provides specific recommendations on the optimal AV parameter settings for different AV penetration levels and traffic scenarios, including a single-lane closure incident. The report does not explicitly mention any potential risks or costs associated with the proposed guidelines. However, it highlights the need for highway agencies to develop effective guidelines to coordinate with the emerging AV flows via the V2I infrastructure, as the impacts of AV flows can vary significantly depending on their driving behavior settings.

The Georgia Institute of Technology developed a driverless vehicle implementation roadmap for the Georgia DOT [89]. The project's overall goal was to guide GDOT in preparing for and adapting to the arrival of AVs. The inputs included a literature review, interviews with industry experts, and focus groups with GDOT leadership and managers. The project used qualitative research methods to synthesize expert opinions and develop recommendations. The roadmap aims to help GDOT anticipate impacts across multiple aspects of AV technology, including planning, operations, infrastructure design, and policy. The report discusses potential benefits like improved safety and mobility, as well as risks such as cybersecurity threats and job displacement. However, specific cost estimates are not provided in this summary. The roadmap emphasizes the uncertainty around AV technology development and deployment timelines, recommending that GDOT take a flexible, adaptive approach rather than making major infrastructure investments prematurely.

Purdue University's CCAT has developed an explainable artificial intelligence framework for autonomous driving systems to enhance user trust in autonomous vehicle operations that rely heavily on AI [90]. From the user's perspective, the provided explanations can enhance trust in the AV system. From the developer's standpoint, the explanations can serve as a "debugging" tool to identify and address potential weaknesses in the existing system. The report does not explicitly mention any potential risks or cost estimates associated with the developed system. However, it highlights the benefits of the explainable DL model in improving situational awareness, driver assistance, and the overall reliability of autonomous systems by providing an extra channel for sanity checks and ensuring the model learns the ideal causal relationships between the driving environment and the vehicle's actions.

The Texas A&M Transportation Institute developed a traffic control infrastructure for autonomous vehicles [91]. The inputs to this project included data from various sources, such as TxDOT and local government Temperament and Character Inventory (TCI) inventory data, as well as third-party TCI digitization data from companies like Mobileye, Blyncsy, and Nexar. The researchers used a variety of AI methods, including computer vision techniques, ML algorithms, and spatial data processing, to extract and analyze the TCI data. The output of this project is a comprehensive TCI dataset that can be used to enhance the safety and operational performance of AVs. The report mentions several potential applications of the TCI digitized data for AVs, including perception, prediction, and planning. For example, AVs can utilize the TCI data to better understand the road network configuration, the presence of traffic signs and signals, and the speed limits, which can improve their driving decision-making and overall safety. Regarding potential risks and benefits, the report identifies several legal issues that may arise from the acquisition, storage, and dissemination of TCI data, such as data privacy, data ownership, and agency liability. However, the report also highlights the potential qualitative and economic benefits of this project, including enhanced safety and customer experience. The economic assessment suggests that the project could lead to a reduction in

AV-related crashes, resulting in an estimated cost savings of over $1.7 million over ten years, with a benefit-cost ratio of 7.71.

The California DOT developed a project to assess the infrastructure needs and requirements for the deployment of AVs [92]. The study involved conducting an online survey and follow-up interviews with 20 companies from the AV industry, including autonomous vehicle startups, technology providers, and traditional automotive manufacturers. The survey and interviews gathered feedback on various aspects of physical and digital infrastructure, such as lane markings, traffic signals, work zone information, and V2X data, and their impact on AV performance. The AV industry expects more stringent infrastructure maintenance requirements for ADS compared to human-driven vehicles, as AVs have limited perception capabilities compared to humans. The industry highlighted issues with interpreting physical infrastructure elements like lane markings, traffic signals, and signage, which can affect ADS performance. Digital infrastructure features like work zone information, traffic signal data, and real-time traffic conditions were identified as important to accelerate ADS deployment. The report did not provide specific cost estimates for the required infrastructure improvements. However, it highlighted the potential risks of infrastructure deterioration and the need for proactive maintenance policies to support safe and efficient AV deployment. The study also recommended increased collaboration between government agencies and the AV industry to address these infrastructure challenges.

Purdue University's CCAT developed a system to improve the transition between AV control and manual takeover [93]. The aim was to study the factors that affect the driver's situational awareness during this critical transition period and to provide inputs for designing an effective SAES. The study used a comprehensive literature review and a driving simulator experiment to explore various risk factors, takeover alert designs, driver attributes, and their impact on situational awareness and takeover performance. The inputs to the study included road environment characteristics (weather, lane markings, construction zones), traffic conditions (density, heterogeneity), driver distraction and impairment, and driver demographic factors. The outputs of this research can inform the design of in-vehicle alerts and human-machine interfaces to effectively direct the driver's attention during critical transitions, thereby promoting a smooth and safe takeover of the AV. The findings can also guide AV manufacturers in specifying user-friendly headways in their control algorithms and help transportation planners update highway capacity analysis to account for the unique characteristics of autonomous mobility. The report did not explicitly mention any major risks or high costs associated with this project. However, it highlighted the importance of continued research in this domain to address the human factors challenges as AVs become more prevalent on public roads. The study represents a valuable contribution towards enhancing the safety and user experience of transitioning between automated and manual driving modes.

The University of Tennessee and Duke University have developed a framework for advancing accelerated testing protocols for the safe and reliable deployment of CAVs [94]. The overall goal of this project is to create a comprehensive testing procedure that can systematically test and certify CAVs to be generally safe for driving on public roads. The project takes a multi-pronged approach, utilizing a combination of techniques. First, it conducts a thorough review of existing AV-involved crashes to identify key factors and scenarios that can be used to develop safety test scenarios. These scenarios cover a wide range of dimensions, including roadway types, traffic conditions, and environmental conditions. The team then uses various simulation tools, such as CARLA, SUMO, and dSPACE, to generate synthetic sensor data that can realistically reproduce the performance of physical sensors like LiDAR, radar, and cameras. This synthetic data is then used in hardware-in-the-loop (HIL) simulations, where actual vehicle hardware is integrated with the simulated environment to measure the vehicle's response and safety performance. The project's outputs are intended to provide insights into the safety envelope of CAVs, particularly in identifying "fringe cases" or edge scenarios where the systems may be prone to failure. This information can be valuable for perception, prediction, and planning algorithms used in CAVs. The report does not explicitly mention the potential risks and benefits or the overall cost of the project. However, the focus on improving the safety of CAVs through rigorous testing and validation suggests that the project aims to address critical challenges and risks associated with the deployment of these technologies. By developing a comprehensive testing framework, the project can potentially contribute to the safe and reliable integration of CAVs into the transportation system, which could offer significant benefits in terms of improved safety, efficiency, and accessibility.

The University of Pennsylvania developed a VR driving simulator to explore the effectiveness of using simulation to educate the public about AVs [95]. The overall goal of this project was to help increase public understanding and trust in AVs by providing an immersive, hands-on experience in a safe and controlled environment. The input to the system was data from 36 participants who had little prior knowledge about AVs. The researchers used a VR driving simulator built on the open-source Carla platform, which allowed participants to experience different driving scenarios involving AVs, such as rural, city, and highway environments. The output was an assessment of how the simulator experience impacted the participants' perceived risk, usefulness, ease of use, trust, and behavioral intention towards AVs. The project utilized various AI methods, including vehicle control, sensor data processing, and environment modeling, to create a realistic AV simulation. The simulation was designed to be highly interactive, allowing participants to switch between manual and autonomous driving modes. This was intended to help participants form a mental model of how AVs operate and understand their capabilities and limitations. The report highlighted several potential benefits of using a driving simulator for AV education, such as providing a safe and flexible environment for testing and demonstration, reaching a wide audience beyond those with driver's licenses, and potentially increasing public trust and acceptance of the technology. However, the report also acknowledged some limitations, such as the simulation environment not fully capturing the complexity of the real world, the need for improved user interaction, and the small sample size of participants. The report did not provide specific cost information for developing and deploying the simulator.

The University of Minnesota developed the MnCAV autonomous vehicle system to investigate the performance characteristics of AVs on highways and local roads in Minnesota [96]. The input to the project was experimental testing of the MnCAV vehicle, which was equipped with various sensors including cameras, radars, and lidars. The team used AI-based methods for perception, such as the Mobileye camera system for lane detection, as well as control algorithms for lateral and longitudinal control of the vehicle. The outputs of the project included assessments of the MnCAV vehicle's performance in different scenarios, including winter driving conditions, vehicle following in traffic, and navigation through work zones. The report highlighted several key findings and recommendations. For winter driving, the team found that even a small amount of snow on the road could significantly impact the lane detection capabilities of the vision-based system, suggesting a need for improved sensing or infrastructure solutions to enable autonomous driving in snowy conditions. In the vehicle following tests, the team demonstrated that the MnCAV vehicle's adaptive cruise control system was capable of attenuating the propagation of acceleration waves through traffic, which could help reduce the severity of traffic backups. However, the report also noted challenges with the MnCAV vehicle's performance in work zone scenarios, where obstacles and conflicting lane markings caused issues for the lateral control system. The report provided valuable insights into the current limitations of autonomous driving systems and suggested areas for future research to address these challenges, which could ultimately lead to safer and more efficient transportation solutions.

Texas A&M University and Virginia Tech developed a project to data mine Twitter to improve AV safety [97]. The overall goal of the project was to understand the influence of AV-related events, such as crashes and technology announcements, on public sentiment and expectations about AVs. The team then conducted topic modeling and sentiment analysis on the collected tweets to understand the most discussed themes, such as crashes, fault and safety, technology companies, and public transit. The findings from the tweet analysis were then translated into a set of guidelines for public information officers (PIOs) to effectively communicate about AV-related events on social media. The report discusses the potential benefits of this approach, such as improving public calibration and subsequent acceptance of AVs through timely and accurate communication. It also highlights the limitations of traditional Twitter analysis techniques, such as the need for domain-specific sentiment dictionaries. While the report does not provide specific cost estimates, it emphasizes the importance of this work in guiding proper public communication to support the safe adoption and use of AV technologies.

Texas A&M University and its partners developed an autonomous vehicle pilot program called ENDEAVRide in small towns in Central Texas [98]. The project aimed to explore public perceptions of AVs. The study utilized survey data, trip logs, focus groups, interviews, and geospatial AI algorithms to collect and analyze data on residents' perceptions, travel behaviors, and traffic safety risks. The outputs included insights on public acceptance of AVs, improved accessibility for older adults and people with disabilities, and a human-centered interactive dashboard for safety data collection and analysis. The findings contribute to the understanding of AV deployment in small towns, particularly in the areas of public perception, mobility enhancement, and safety assessment. The report highlighted potential benefits such as increased independence for older adults and individuals with disabilities, reduced air pollution, and improved fuel efficiency. However, concerns were raised regarding job loss in the driver industry, increased trip frequency and duration, and reduced walking. The study also identified factors influencing the alignment between perceived and objective traffic safety risks. While the report did not provide specific cost information, it emphasized the importance of strong partnerships among local stakeholders, nonprofits, and the industry in sustaining innovative programs like ENDEAVRide.

The University of Michigan developed an integrated AR testing environment for AVs and implemented it at the American Center for Mobility (ACM) [99]. The project's overall goal was to create a high-fidelity simulation environment that combines a naturalistic driving environment (NDE) with an AR testing system to evaluate AV safety performance more efficiently and accurately in closed testing facilities. The input for the system is large-scale naturalistic driving data (NDD) collected by UMTRI, which is used to generate realistic human driving behaviors in the NDE. The project employed data-driven and optimization-based methods to create empirical behavior models and refine them to minimize accumulated errors. The output is a distributionally consistent NDE that can generate realistic traffic conditions, including vehicle speeds, range distributions, and lane-changing statistics. The integrated AR testing environment is used for testing and evaluating AV safety performance, particularly in the areas of perception, prediction, and planning. The report mentions that the proposed system has the potential to increase the efficiency of AV performance testing, reduce operational costs, and accelerate product validation. However, the report does not provide specific information on the potential risks or the cost of implementing the integrated AR testing environment.

The University at Buffalo and the New York State DOT, developed a project to evaluate and test the Olli self-driving electric shuttle on the university's North Campus [100]. The project's overall goal was to assess the technical feasibility, safety, and reliability of using autonomous vehicle (AV) technology for passenger transportation, particularly in a campus setting. The project involved testing the Olli shuttle on a designated proving ground collecting and analyzing data from various sensors and systems onboard the vehicle. The research team used simulation modeling and real-world testing to evaluate the shuttle's performance in different scenarios, including interactions with pedestrians, other vehicles, and various traffic conditions. The project addressed multiple aspects of AV technology, including perception, planning, and control algorithms. Additionally, the researchers examined public acceptance of AVs through surveys and demonstrations and investigated the regulatory and policy implications of deploying AVs on public roads. The report mentions potential benefits such as improved safety, increased mobility, and reduced traffic congestion while also acknowledging risks related to public acceptance and regulatory challenges. The project included a case study for the Buffalo Niagara Medical Campus, estimating the cost of operating a fleet of five Olli shuttles to be approximately $1,365,000 per year under a public plan. However, the report does not provide a comprehensive cost-benefit analysis or detailed risk assessment for the broader implementation of AV technology.

Figure A6 summarizes the aforementioned initiatives regarding autonomous vehicles. These works and projects generally highlight significant potential benefits of AV technology, including improved safety, enhanced mobility, reduced traffic congestion, and increased fuel efficiency. Many studies emphasize the potential for AVs to reduce crashes, improve travel times, and lower operating costs. Some projects also note the potential for increased independence for older adults and individuals with disabilities. However, these benefits come with several risks and challenges. Cybersecurity threats, job displacement in the driver industry, and public acceptance issues are commonly cited concerns. Technical challenges include the need to address domain adaptation, stability, and transparency issues in AI algorithms, as well as improving AV performance in adverse weather conditions like snow. Legal and regulatory challenges, particularly around data privacy, ownership, and agency liability, are also noted. While specific cost estimates are not provided for many projects, one case study estimated the annual cost of operating a fleet of five autonomous shuttles at approximately $1,365,000. Another project suggested potential cost savings of over $1.7 million over ten years from reduced AV-related crashes, with a benefit-cost ratio of 7.71. Many reports emphasize the need for continued research, flexible policy approaches, and collaboration between government agencies and the AV industry. They also stress the importance of public education and communication to build trust and acceptance of AV technology. Overall, while the potential benefits of AVs are significant, the reports indicate that careful consideration of risks, costs, and implementation strategies is crucial for successful deployment.

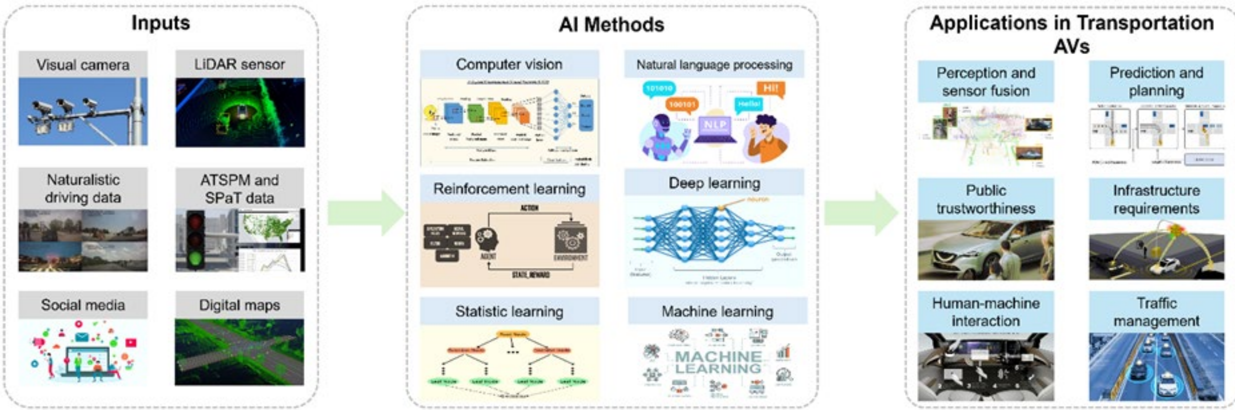


Figure A6 AI-Driven Methods and Applications for Enhancing Autonomous Vehicles.

Generative AI

Generative Artificial Intelligence (Generative AI) is an advanced technology that enables machines to create original content, like writing, images, and music, by learning patterns from existing data and generating new outputs based on that knowledge. Key technologies driving this field, such as Variational Auto-Encoder (VAE), Generative Adversarial Network (GAN), Energy-Based Models (EBMs), and Generative Pre-trained Transformer (GPT), provide substantial benefits for generating, transforming, and refining large and complex datasets [101], [102], [103], [104]. Additionally, they are highly effective in modeling data uncertainty. Figure 8 provides an overview of AI-driven methods and applications for generative AI in transportation.

Generative AI offers significant potential to revolutionize the transportation industry by providing innovative ways to tackle traffic issues. For instance, in autonomous driving, Generative AI is crucial for creating high-quality driving scene images and videos, which play a key role in training and evaluating autonomous driving systems [105]. By simulating driving scenarios, autonomous vehicles can engage in extensive virtual simulations, enhancing their ability to make accurate decisions in real-world situations. Additionally, for tasks like predicting traffic flow, Generative AI can learn from existing traffic data to forecast future traffic patterns more effectively [106].

Researchers have investigated the use of generative AI in areas such as traffic perception, prediction, simulation, and decision-making [107]. Traffic perception is the capability of the transportation systems to gather and interpret sensory information from the traffic environment, such as visual information, vehicle trajectories, motion, and environmental conditions. This is especially critical for autonomous vehicles, which rely on technologies like cameras, LiDAR, and radar to process their surroundings. However, challenges arise due to data gaps from obstructed sensors, noise from weather or lighting conditions, and the complexity of traffic environments. Generative AI offers potential solutions to these challenges by improving data imputation, traffic estimation, and anomaly detection. Traffic prediction involves estimating future traffic conditions, including travel demand, time, flow, and the movements of vehicles and people. It is essential for effective urban traffic planning but faces challenges due to the complexity of traffic systems, their dynamic nature, and the difficulty in obtaining complete, high-quality data. Generative AI offers solutions to these issues by improving prediction accuracy. Traffic simulation models the movement and behavior of vehicles and pedestrians for use in urban planning, policy evaluation, and autonomous vehicle testing. However, realistic simulations face challenges, including the high cost and difficulty of obtaining real-world traffic data, especially in rare or dangerous situations, and the complexity of traffic dynamics due to factors like driver behavior, weather, and infrastructure interactions. Traditional deep learning models often need large amounts of labeled data and struggle with rare scenarios [108]. Generative AI offers solutions by creating realistic traffic scenarios, simulating rare events, and continuously refining simulations with minimal real data. Generative AI is enhancing traffic decision-making in autonomous driving by creating realistic and diverse traffic scenarios for training systems, which helps vehicles handle unpredictable situations more effectively. It can simulate rare but critical events, like sudden pedestrian crossings or mechanical failures, providing valuable training data that is not often or difficult to see in real-world scenarios. Additionally, generative AI improves decision-making by generating enhanced sensor data, allowing vehicles to adapt better to challenging environments such as fog or rain, ultimately making autonomous driving safer and more reliable in complex traffic situations.

In recent developments, California's Department of Transportation awarded the first-ever Generative AI contract in the state's history to Inrix, a transportation data and software company [109]. Caltrans is seeking GenAI solutions to enhance vulnerable roadway user safety and process and interpret diverse data to provide Traffic Mobility Insights. The Inrix Compass software uses real-time and historical traffic data, along with statewide datasets on crashes and roadway inventories, to assess risk and provide project recommendations. According to Inrix, this technology will enable California transportation officials to make predictions about every functional road in the state, from rural highways to busy urban thoroughfares. In 2020, Inrix launched a new Generative AI-powered product aimed at helping cities manage traffic flow more effectively. That same year, transportation departments in five states—Louisiana, Oregon, Tennessee, Texas, and Rhode Island—adopted Inrix's real-time traffic data to alleviate congestion, lower air pollution, and prevent roadway fatalities [110].

Consultants from Deloitte believe that generative AI could also be transformative in transportation logistics management [111]. Based on their discussion, Generative AI can significantly enhance transportation management by streamlining carrier onboarding through automated verification of credentials and performance evaluations, enabling real-time communication and collaboration between carriers and shippers, and optimizing route planning based on AI-driven insights. It can also automate comprehensive freight audits, ensuring accuracy and compliance in financial transactions while transforming reporting capabilities by generating custom, real-time reports and offering predictive analytics for improved decision-making and operational efficiency.

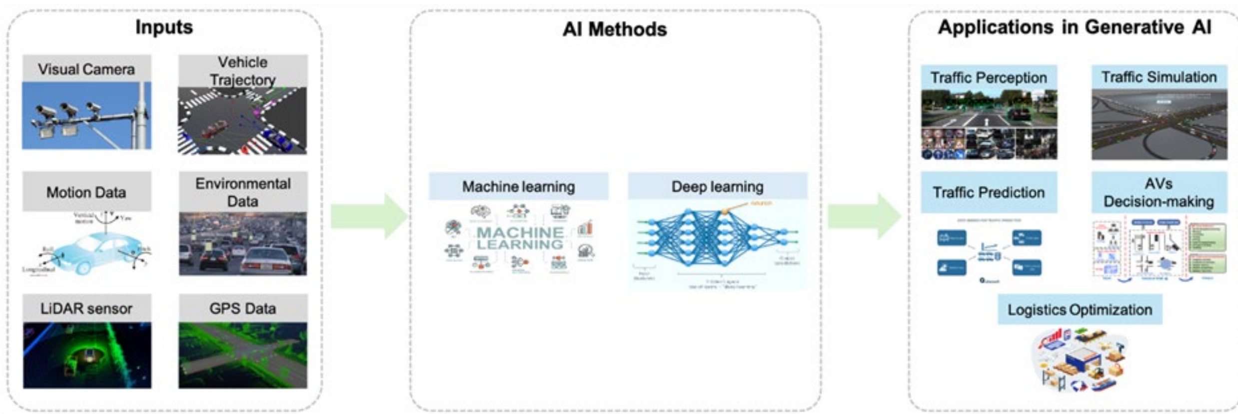


Figure A7 AI-Driven Methods and Applications for Generative AI.

Generative AI offers benefits in transportation by enhancing traffic prediction, simulation, and decision-making, particularly in autonomous driving. It improves data imputation, anomaly detection, and the modeling of complex traffic environments, providing more accurate forecasts and creating realistic simulations for training. Generative AI can handle rare events and unpredictable scenarios, improving safety and reliability in autonomous systems. Additionally, it streamlines transportation logistics management by automating processes such as carrier onboarding, freight audits, and real-time communication, enabling better resource optimization and operational efficiency.

Implementing generative AI in transportation presents several challenges. First, using multi-modal traffic data is difficult due to the need for accurate alignment between diverse data sources like camera images, weather information, and sensor data. This requires advanced techniques to handle complex data correlations and maximize consistency across modalities. Second, capturing the intricate spatio-temporal dynamics of traffic—how traffic patterns change over time and space—is a challenge that current models struggle to fully address. Third, generative AI models face difficulties when dealing with sparse or missing data, as they may generate plausible but inconsistent data or neglect rare traffic patterns, reducing the diversity and accuracy of their outputs. Additionally, generative AI systems are vulnerable to adversarial attacks, which could compromise safety by manipulating traffic decisions, and these attacks are hard to detect. Another key challenge is model interpretability—explaining how generative AI makes decisions, especially in complex scenarios like autonomous driving, is difficult, as these models often operate as black boxes. Lastly, meeting real-time requirements is a challenge due to the computational complexity of generative models, which must balance accuracy and speed to make split-second decisions in dynamic traffic conditions while also handling noisy or incomplete data.

APPENDIX B: SURVEY DETAIL

We invite you to participate in a survey for the Wisconsin Department of Transportation (WisDOT) Policy Research Program: Artificial Intelligence (AI) in Transportation. This study is led by the University of Wisconsin-Madison and the University of Wisconsin-Milwaukee. Your participation in this research study is voluntary, and you may stop at any point or choose not to answer specific questions. Your responses will help researchers who aim to better understand AI applications' current practices, benefits, and challenges. Your insights are crucial for shaping the future of AI adoption and its integration into WisDOT.

If you have any questions regarding this study, please review the full content form. You should feel free to reach out to one of the research investigators. Principle Investigator (PI): Sikai Chen, Ph.D. E-mail and Phone: sikai.chen@wisc.edu | (213) 806-0141.

"I have read the conditions of this study and have had all my questions answered. I hereby acknowledge the above and give my voluntary consent to participate in this study":

[To affirm your consent, please click next.]

Next →

Part I: Basic Information

This section asks for general information about you and your organization, such as the type of agency you work for, your role, and some basic demographics. This information helps us understand the background of each participant, allowing us to see how responses may differ based on factors like agency type or location. Collecting this information helps us better analyze and compare perspectives on AI use in transportation across different organizations and regions. Please note that basic demographic data will only be used to ensure that we have a representative sample.

1.1. Please provide the name of your organization:

1.2. What type of agency do you represent?

- ◯ State department of transportation
- ◯ Federal agency
- ◯ Local agency (city/county)
- ◯ Technology provider
- ◯ Academic/Research institution
- ◯ Professional committee
- ◯ Other (please specify)

1.3. In which geographic region is your organization based?

- ◯ Northeast (New England and Middle Atlantic)
- ◯ Midwest (East North Central and West North Central)
- ◯ South (South Atlantic, East South Central, and West South Central)
- ◯ West (Mountain and Pacific)

1.4. Please provide what part of the organization your position is in (e.g., office, division, bureau, or section).

- ◯ Operations
- ◯ Planning and Design
- ◯ Safety and Enforcement
- ◯ Research
- ◯ Maintenance and Infrastructure
- ◯ Policy and Administration
- ◯ Other (please specify)

1.5. What is your gender?

- ◯ Male
- ◯ Female
- ◯ Non-binary / gender nonconforming
- ◯ Prefer not to say

1.6. What is your age?

- ◯ Under 25
- ◯ 25 - 35
- ◯ 36 - 50
- ◯ 51 - 60
- ◯ Over 60
- ◯ Prefer not to say

1.7. What is the highest level of education you have completed?

- ◯ High school diploma or equivalent
- ◯ Associate Degree
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ Doctorate

1.8. How long have you been working in your current position?

- ◯ Less than 5 years
- ◯ 5-10 years
- ◯ 11-15 years
- ◯ 16-20 years
- ◯ More than 20 years

1.9. Have you been involved in any AI-related applications?

- ◯ Yes
- ◯ No

Part II: Questions of AI Applications in Transportation

This section examines the practical applications, benefits, and challenges of implementing AI in transportation. It assesses the effectiveness and potential impact of AI in areas such as asset management, safety, and operations, while also addressing key obstacles, including data privacy, cybersecurity, and public acceptance. This evaluation aims to identify critical success factors and barriers to AI adoption within transportation agencies. This part contains three subsections:

2.1 Application Areas
2.2 Data Management
2.3 Infrastructure for Supporting AI

2.1 Application Areas

This subsection explores the various AI application areas within transportation, aiming to assess their potential, effectiveness, expected benefits, and associated challenges.

2.1.1. Please provide your inputs to the following table (click each category for more information)

	If this application area has been implemented in your organization, how satisfied are you with its performance? (1 = Not satisfied, 5 = Highly satisfied; select NA if not applicable)	How familiar are you with this application? (1 = Not at all familiar, 5 = Extremely familiar)	Expected timeframe to demonstrate benefits—short-term (1-3 years), medium-term (4-7 years), or long-term (8+ years); select NA if not applicable	Rate the potential benefits of each application from 1 to 5 (1 = Very low benefit and 5 = Very high benefit).	Rate the challenges and risks of each application from 1 to 5 (1 = Very low risk and 5 = Very high risk).
- Transportation Asset Management					
- Transportation safety					
- Transportation Operations					
- Digital Twins					
- Autonomous Vehicles					
- Generative AI					

2.1.2. Is your agency using AI in any other application areas not covered above? If so, how?

2.1.3. What is your agency's current approach to AI deployment? (Check all that apply)

- [ ] Commercial off-the-shelf software purchase
- [ ] In-house development
- [ ] External contractor development
- [ ] Hybrid approach (combination of internal and external resources)
- [ ] Partnership with academic institutions
- [ ] Unsure
- [ ] Other (please specify):

2.1.4. Are there any specific security, data privacy, or ethical concerns your organization has encountered when implementing AI applications? How are these concerns addressed?

2.2 Data Management

This subsection examines the types of data used in AI applications, the quality and management of that data, and the challenges involved in data-related tasks. It aims to identify data quality, sources, and management issues, which are critical for effective AI deployment in transportation.

	Select the data that your agency uses for AI applications	Rate the quality of data. (1 = worst, 5 = best; select NA if not applicable)	How challenging are data collection, when applied to the respective data type? (1 = Not challenging, 5 = Extremely challenging)	How challenging are data cleaning, when applied to the respective data type? (1 = Not challenging, 5 = Extremely challenging)	How challenging are data labeling, when applied to the respective data type? (1 = Not challenging, 5 = Extremely challenging)	How challenging are data management, when applied to the respective data type? (1 = Not challenging, 5 = Extremely challenging)
- Vision data (e.g., cameras, LiDARs)	☐					
- Text data (e.g., social media data, police reports)	☐					
- Map data (e.g., HERE map, Google Map, GIS)	☐					
- Traffic data (e.g., traffic speed, volume, occupancy, telematics)	☐					
- Other (please specify):	☐					

2.3 Infrastructure for Supporting AI

This section assesses the infrastructure needed to integrate AI with existing systems and maintain performance under challenging conditions. It helps to understand the technical and environmental barriers that may impact AI effectiveness in transportation contexts.

2.3.1. Rate the challenges faced in integrating AI with existing transportation infrastructure:
(1 = Not challenging, 5 = Extremely challenging)

	1	2	3	4	5	Do not know
Compatibility with legacy systems (e.g., traffic cameras, signals, and network):	○	○	○	○	○	○
Real-time data processing:	○	○	○	○	○	○
Scalability of AI solutions:	○	○	○	○	○	○
Maintenance of AI-integrated systems:	○	○	○	○	○	○
Training staff on new AI-enhanced infrastructure:	○	○	○	○	○	○
Maintaining data security	○	○	○	○	○	○

2.3.2. What issues have you encountered in using AI applications (check all that apply)? How frequently do you encounter the issues you selected? (1 = infrequent, 5 = extremely frequent)

	1	2	3	4	5	Do not know
- Hardware failures due to severe conditions	○	○	○	○	○	○
- Communication disruptions	○	○	○	○	○	○
- Power outages affecting AI systems	○	○	○	○	○	○
- Reduced sensor accuracy in extreme conditions	○	○	○	○	○	○
- High maintenance costs	○	○	○	○	○	○
- Difficulty finding appropriate training data	○	○	○	○	○	○
- Increased data processing demands	○	○	○	○	○	○
- Difficulty in real-time decision making	○	○	○	○	○	○
- Limited historical data for rare weather events	○	○	○	○	○	○
- Lack of employees trained in using AI tools/systems	○	○	○	○	○	○
- Other (please specify):	○	○	○	○	○	○

Part III: Cost and Workforce Development

This section examines the cost-effectiveness, financial considerations, and workforce implications of implementing AI. It assesses the economic impact of AI adoption, evaluating cost-related factors that influence its sustainability, while also addressing training efforts, skill requirements, and workforce development needs to bridge skill gaps and ensure effective AI integration and management within organizations.

3.1. Have you or your organization performed any study or evaluation on the cost-effectiveness of AI applications?

- ◯ Yes
- ◯ No

3.2. Rate the significance of the following cost factors in your AI projects:
(1 = Not significant, 5 = Highly significant)

	1	2	3	4	5
- Initial hardware/infrastructure costs:	◯	◯	◯	◯	◯
- Software licensing fees:	◯	◯	◯	◯	◯
- Data acquisition and preparation:	◯	◯	◯	◯	◯
- AI model development and training:	◯	◯	◯	◯	◯
- System integration:	◯	◯	◯	◯	◯
- Ongoing maintenance and updates:	◯	◯	◯	◯	◯
- Staff training:	◯	◯	◯	◯	◯

3.3. Does your organization offer AI-related training programs for employees? What areas do these training programs cover?

- [ ] AI introduction and relevant theories
- [ ] Data ethics and security
- [ ] AI tools and platforms.
- [ ] Others (Please specify)

- [ ] No AI-related training

3.4. What areas do you see as having the greatest gap between current and needed skills for AI applications?

- [ ] Technical skills
- [ ] Data management
- [ ] Legal and ethical knowledge
- [ ] Understanding of AI's social impacts
- [ ] Hands-on experience with AI applications
- [ ] Others (Please specify)

3.5. On average, how many hours do you receive annually for each of the following training formats associated with AI?

	Less than 10 hours	10-20 hours	21-40 hours	41-80 hours	More than 80 hours
- Professional Conferences	○	○	○	○	○
- Webinars (e.g. TRB, NCHRP, U.S. DOT)	○	○	○	○	○
- Vendor presentations	○	○	○	○	○
- In-house training	○	○	○	○	○
- Certificate program (e.g., Machine learning certification, AI certification)	○	○	○	○	○
- Others (Please specify)	○	○	○	○	○

3.6. How effective do you feel the current AI-related training programs are in preparing employees for their roles? (1 = Ineffective, 5 = Extremely effective)

1	2	3	4	5
○	○	○	○	○

3.7. What actions do you think WisDOT should prioritize to prepare for widespread AI adoption? (Check all that apply)

- [ ] Developing AI-specific policies
- [ ] Enhancing technical infrastructure
- [ ] Providing AI-focused training programs
- [ ] Establishing robust data management systems
- [ ] Addressing security and ethical concerns
- [ ] Other (please specify):

3.8. Please provide any additional comments or insights about your experience with AI in transportation:

3.9. Would you be willing to be contacted for a follow-up interview to discuss your responses in more detail, or you want to receive a copy of the survey summary? If yes, please provide your preferred contact information (optional):

APPENDIX C: DETAILED INSIGHTS FROM FOLLOW-UP INTERVIEW

1. Motivations and Strategic Approaches to AI Adoption

The interviews revealed diverse strategic approaches to AI adoption in transportation agencies. While some DOTs like Texas DOT (TxDOT) have developed formal AI strategic plans through extensive stakeholder engagement, others are pursuing more opportunistic, pilot-based approaches. TxDOT's strategic data scientist described a comprehensive process involving focus groups with 91 attendees across district divisions, resulting in a three-year strategic plan with prioritized use cases based on stakeholder votes. This structured approach aligns with our survey findings in Section 4.1, where providing AI-focused training programs and developing AI-specific policies were identified as top priorities.

Professionals from the private sector provided complementary insights into how consulting firms are helping shape AI readiness. A Stantec representative highlighted that while many public agencies remain cautious, consultants are seeing increasing demand for AI-supported design workflows. Their internal initiatives have already tested DevOps pipelines and generative design tools to automate highway modeling and plan validation. HDR echoed this trend, emphasizing that real-time traffic management tools—like adaptive signal control and video-based pedestrian detection—are pushing the boundaries of what's feasible with AI in live environments.

Also, AI adoption was primarily driven by operational efficiency goals rather than purely academic interest. FDOT focused on improving efficiency and cost management in resurfacing projects, while GDOT initiated AI exploration through both policy development and pilot use cases to better understand capabilities and risks. WSDOT highlighted the potential of AI to transform massive amounts of manually processed field data into proactive decision-making tools, particularly for asset management and safety applications. This pragmatic approach aligns with our survey findings in Section 4.1, where we found that most transportation professionals (86.8%) have engaged with AI applications, but the majority (70.8%) have less than 5 years of experience, indicating that AI adoption in transportation is still in relatively early stages.

Consulting professionals working with DOTs noted that many agencies are still in the "late adopter" phase but recognize the potential of AI for processing vast amounts of field data. As one consultant mentioned, transportation agencies are increasingly seeing AI as a tool to achieve "more proactive decision-making, particularly for asset management and safety." This observation supports our survey results in Section 4.2.4, which identified these domains as having high benefit potential and shorter implementation timeframes.

The GDOT representative highlighted an iterative approach that combines policy development with practical implementation: "Be willing to enter the AI space at several levels simultaneously. Needing a policy statement before doing anything will not be very effective." This balanced approach of developing governance frameworks while gaining practical experience through pilots reflects the dual priorities identified in our survey, where both policy development (66.7%) and training programs (77.8%) were highly endorsed.

The interviews revealed a common pattern of pragmatic, phased implementation approaches. Rather than pursuing comprehensive AI transformation, these agencies favored targeted use cases with clear operational benefits. As the GDOT representative advised, agencies should "start AI initiatives across multiple levels at once—policy, pilots, and operations" rather than waiting for perfect policy frameworks before implementation. This iterative approach allows agencies to learn from practical applications while simultaneously developing governance structures.

2. Primary Application Areas and Implementation Results

The follow-up interviews revealed a clear pattern of AI applications that closely aligns with our survey findings in Section 4.2.4 regarding high-value, near-term application areas. Traffic operations, safety, and asset management emerged as consistent focus areas across multiple agencies.

In traffic operations, several interviewees highlighted signal control optimization and traffic management applications. One consultant described Las Vegas's implementation of the Derq system, which uses video cameras and edge computing at 10-20 intersections to "improve safety and reduce delay by approximately 20%." GDOT has developed a retrieval-based system to help Traffic Management Center operators quickly access standard operating procedures (SOPs) from poorly organized documentation—a practical application of generative AI for knowledge management.

Asset management applications were equally prominent. TxDOT reported using connected vehicle data to predict battery failures with 96% accuracy, enabling proactive maintenance scheduling. Several interviewees mentioned automated asset inventory using computer vision, with one consultant noting their work on "origin-destination studies" and "sight design optimization." These applications directly support our finding in Section 4.2.1 that Map data and Traffic data are considered high-quality, low-difficulty data sources for AI implementation.

The interviews also highlighted innovative applications in engineering and design processes. One consultant described using generative AI to design "90% with prompts and background data" and developing a tool to convert CAD to GIS for land acquisition tracking. TxDOT has implemented a predictive tool for estimating labor hours for engineering contracts, addressing what one interviewee described as an "unlikeable task that might contribute to poor or inconsistent quality" when done manually. These examples demonstrate how AI can not only improve operational efficiency but also enhance decision quality in complex domains.

HDR's experience with edge AI in Las Vegas—through the Derq system—demonstrates how AI can meaningfully reduce traffic delay (~20%) and improve pedestrian safety. The system combines real-time video analytics with adaptive control hardware installed at intersections. Meanwhile, Stantec has used generative AI for preliminary design automation, claiming up to 90% design generation completeness from structured prompts. They've also worked on CAD-to-GIS conversion tools to support land acquisition planning, examples that show AI's potential in both civil engineering and data integration contexts.

FDOT has made significant progress in pavement condition forecasting using machine learning models for raveling detection, which were refined over several years to improve classification accuracy. They also began automating crack and ride rating detection while maintaining quality assurance through manual verification. Similarly, WSDOT has explored AI in pavement and geotechnical asset management, developing predictive models to support maintenance planning.

A common theme across agencies was the evolution from initial experimental models to increasingly refined systems through iterative improvement cycles. As the FDOT representative noted, their machine learning models required multiple iterations as initial algorithms "underperformed for severe cases, necessitating retraining and supplemental data collection." This reflects the importance of continuous learning and adaptation in AI implementation.

3. Data Quality Challenges and Management Strategies

Data quality emerged as a critical challenge across all interviews, strongly reinforcing our survey findings in Section 4.2.1 about data preparation difficulties. TxDOT's strategic data scientist specifically highlighted the challenge of inconsistent data formats, noting that "highway names have 15 variations of the same highway in the database," requiring extensive cleanup for string matching. FDOT encountered issues with underrepresented categories in training datasets, requiring continuous data collection and labeling to improve model accuracy. GDOT noted that their SOP documentation, while valuable, was poorly structured, and older infrastructure data was often outdated or incomplete, complicating digital twin applications. WSDOT similarly highlighted that legacy data frequently lacks the detail necessary for effective AI models.

The interviewees consistently emphasized the importance of data collection and preparation as foundational to successful AI implementation. One consultant mentioned that for asset management applications, "good models require current and comprehensive data," while another noted that "legacy data often lacks detail," complicating digital twin development. WSDOT's representative emphasized that transportation agencies must "prioritize investments in data infrastructure to support scalable AI solutions."

These findings strongly corroborate our survey results in Section 4.2.1, which indicated varying levels of data preparation difficulty across different data types. Specifically, our survey found that Text data presented significant challenges in data cleaning, while Vision data posed difficulties in data labeling—issues directly experienced by the interviewed agencies. Additionally, half of all survey respondents (50.0%) identified data management skills as a significant skills gap, as noted in Section 4.1.6, further emphasizing the critical importance of data quality in successful AI implementation. These observations also directly support our survey finding that establishing robust data management systems was one of the top three recommended actions for transportation agencies. The interviews provided concrete examples of how data quality issues can undermine AI effectiveness, with one consultant noting that their machine learning model for raveling detection "underperformed for severe cases, necessitating retraining and supplemental data collection."

To address these challenges, agencies have adopted proactive data management strategies. WSDOT, for instance, updates its pavement data annually to ensure current information for their predictive models. FDOT emphasized the importance of supplemental data collection to address gaps in training datasets, particularly for severe cases that were initially underrepresented. These findings reinforce our survey results regarding data management as a critical foundation for successful AI implementation. As the WSDOT representative emphasized, “AI tools are only as effective as the data feeding them,” suggesting that transportation agencies should prioritize investments in data infrastructure before pursuing advanced AI applications.

4. Risk Perception and Mitigation Strategies

The follow-up interviews provided nuanced perspectives on risk perception that aligned with our survey findings in Section 4.2.3 regarding the relationship between experience and risk awareness. Several interviewees confirmed that deeper understanding of AI technologies often leads to greater risk recognition. The FDOT representative noted that deeper exposure reveals more nuanced risks, particularly around financial accountability and data bias. The GDOT representative acknowledged that while AI has potential, "assumptions in the data and over-trust in outputs pose real risks." WSDOT similarly highlighted concerns about generative AI hallucinations and poor model performance resulting from inadequate data quality. One consultant explicitly voiced concern about "people who use generative AI but don't understand the statistical model, trust it implicitly," while another worried about potential "overreliance on AI outputs and poor results due to data inconsistencies." These comments directly support our survey finding that professionals with more limited AI experience (Group 1) often demonstrate greater skepticism toward emerging AI applications.

To mitigate these risks, agencies emphasized the importance of human oversight in AI implementations. FDOT maintains strong quality assurance processes despite automation, suggesting a hybrid validation model. GDOT focuses on tools that support rather than replace decision-making, particularly for repetitive tasks. WSDOT stressed that final decisions should still rest with human experts, especially for safety-critical applications.

The agencies also reported evolving governance frameworks to address data privacy and security concerns. GDOT avoids recording video to mitigate personally identifiable information (PII) risks, while WSDOT discourages the use of external tools like ChatGPT due to data leakage concerns. These approaches reflect the need for transportation agencies to develop robust data governance policies alongside AI implementation.

5. Workforce Development and Training Approaches

The interviews revealed that workforce development for AI remains an emerging priority across transportation agencies, consistent with our survey findings in Section 4.1.4 that nearly half of respondents (48.3%) reported receiving no formal AI-related training. Several interviewees described early-stage or informal training approaches, with TxDOT recently launching an "AI 101 course" in December 2024, covering basic AI concepts, machine learning, and generative AI. At FDOT, AI training is informal and decentralized, with most knowledge transfer occurring through hands-on involvement in data collection and system development. GDOT acknowledged being early in the process and is looking to peer agencies for guidance. WSDOT reported agency-wide efforts as still in early stages, with discussions around tools like GitHub Copilot but no formal training programs in place.

The WSDOT representative highlighted the need for change management and practical user training, such as prompt engineering for generative AI applications. This aligns with our survey's emphasis on providing AI-focused training programs as the most widely endorsed recommendation for enhancing organizational AI readiness. Private sector organizations appear somewhat more advanced in their training approaches, though challenges remain. One consultant mentioned that their firm "bought 10,000 copilot licenses, didn't use them because of fear," highlighting the importance of change management alongside technical training. Another noted that most AI knowledge transfer occurs through "hands-on involvement in data collection and system development" rather than formal programs.

These observations align with our survey finding that technical skills (73.3%) and hands-on experience (66.7%) represent the most significant AI skills gaps in the transportation sector. The interviews suggest that addressing these gaps requires both structured training programs and practical application opportunities. As one consultant emphasized, "change management and training are important" for successful AI adoption, requiring "buy-in from leadership."

6. Effective Partnerships and Collaboration Models

The interviews provided insights into different collaboration models for AI development. FDOT reported strong internal collaboration with materials and asset management teams, as well as partnerships with manufacturers and equipment integrators for hardware/software alignment. GDOT's efforts have primarily been with private vendors, with limited academic partnerships due to slow research timelines, though this flexibility is improving. One consultant similarly noted that vendor collaboration has "advanced AI pilots faster than academia."

However, other interviewees emphasized the value of diverse partnerships, with one suggesting that "a mix of academics and industry people" works well. TxDOT's strategic data scientist mentioned using enterprise data platforms like Jupyter notebooks for internal development, suggesting that in-house capabilities can complement external partnerships. WSDOT expressed interest in university collaborations but has not yet established formal agency partnerships for AI development.

The interviews highlighted specific examples of effective collaboration, including partnerships with technology providers like Derq for edge computing applications and firms like Stantec for flood prediction tools. These case studies suggest that transportation agencies might benefit from a diversified partnership approach, combining internal cross-functional teams, vendor relationships for immediate implementation needs, and academic collaborations for longer-term research.

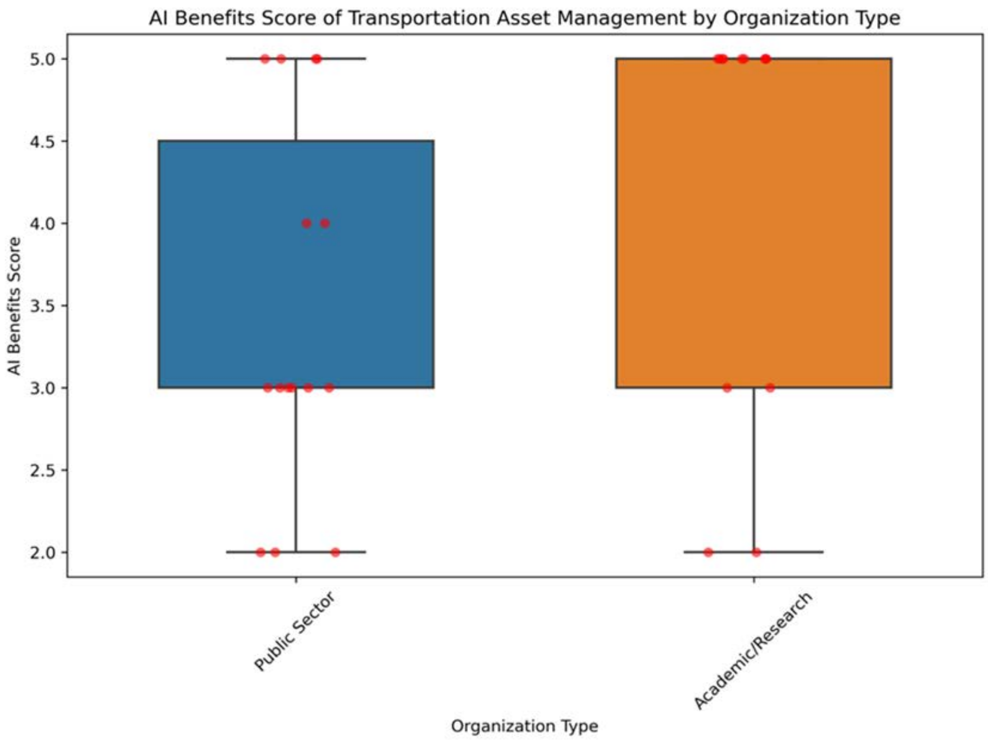
7. Governance, Ethics, and Accountability

The follow-up interviews provided valuable insights into emerging governance frameworks for AI in transportation agencies. Several interviewees described developing formal AI policies, with one consultant noting requirements that "anything output from AI has to be quality controlled" and another mentioning policies against "uploading sensitive information" to LLMs.

Data privacy emerged as a particular concern, with one interviewee noting that their agency "doesn't record any video to protect PII." Another emphasized the importance of ensuring attribution in AI-generated content, noting that for their Retrieval Augmented Generation (RAG) application, they "need to make sure the citations are correct and accurate."

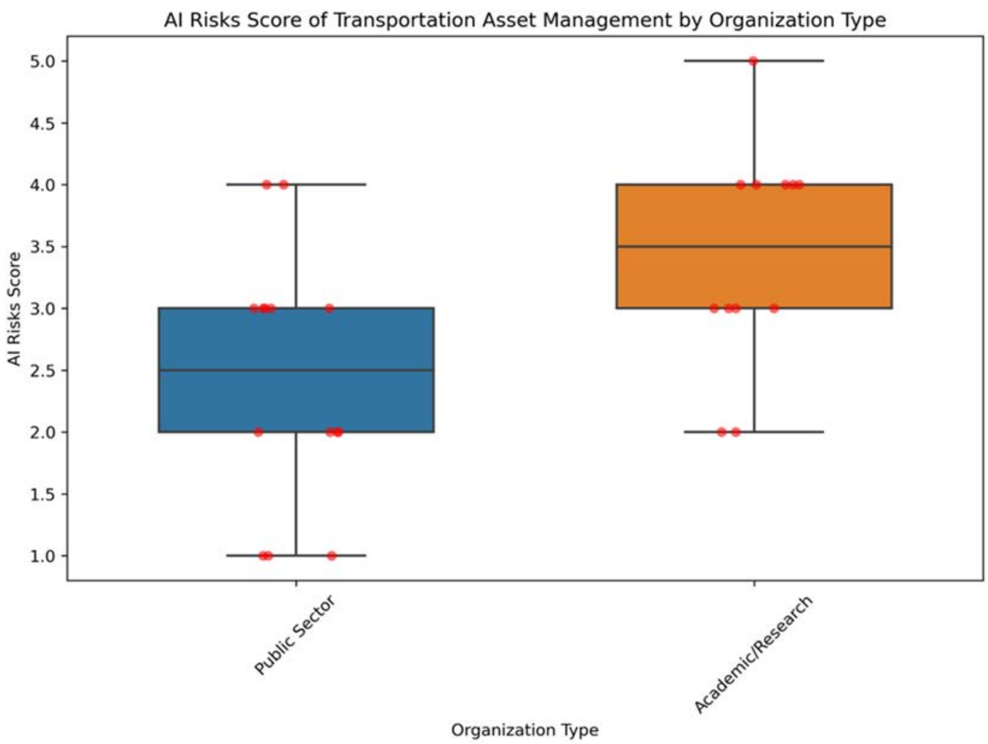
These governance approaches align with our survey finding in Section 4.1.7 that addressing security and ethical concerns was endorsed by 59.3% of respondents as a priority action. The interviews suggest that transportation agencies are developing policies that balance innovation with appropriate safeguards, focusing particularly on data privacy, decision accountability, and transparency in AI use.

APPENDIX D: SUPPLEMENTARY FIGURES



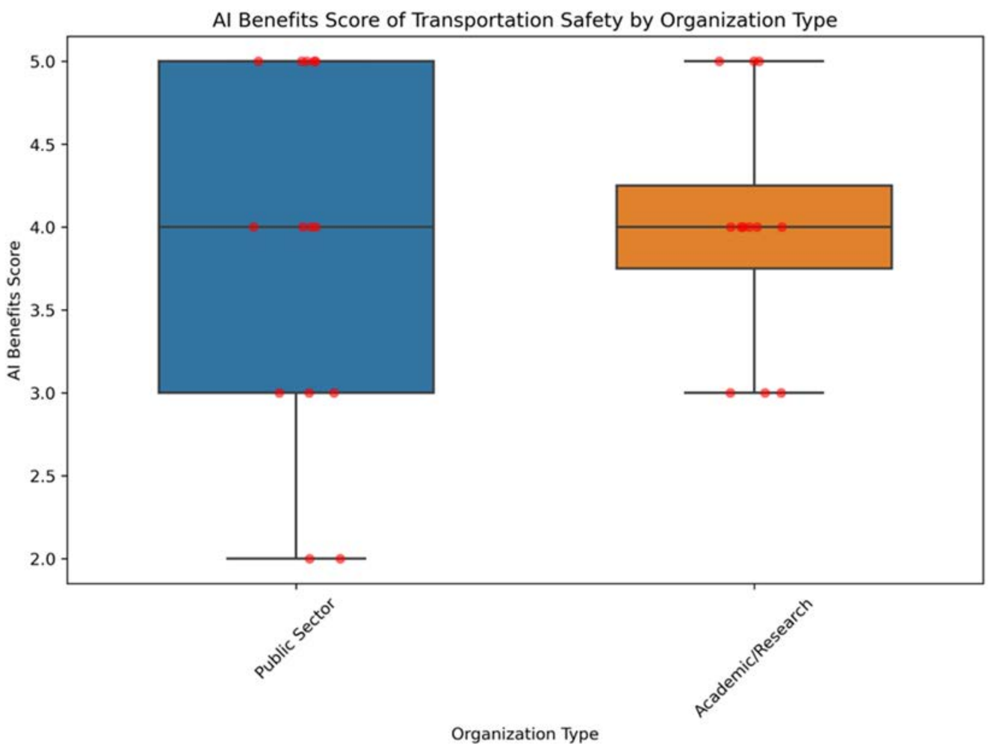
ANOVA Results: F=2.93, p=0.099, No significant difference

Figure D1 Differences of AI Benefits by Organization Type - Transportation Asset Management



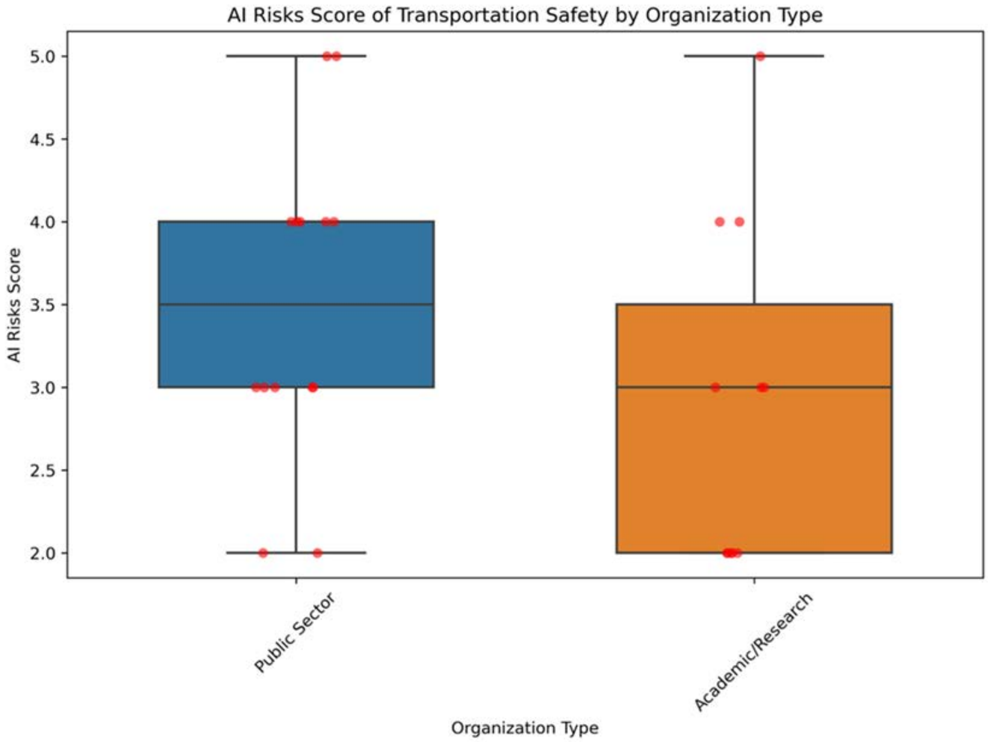
Turkey HSD test results: p=0.016, Significant difference

Figure D2 Differences of AI Risks by Organization Type - Transportation Asset Management



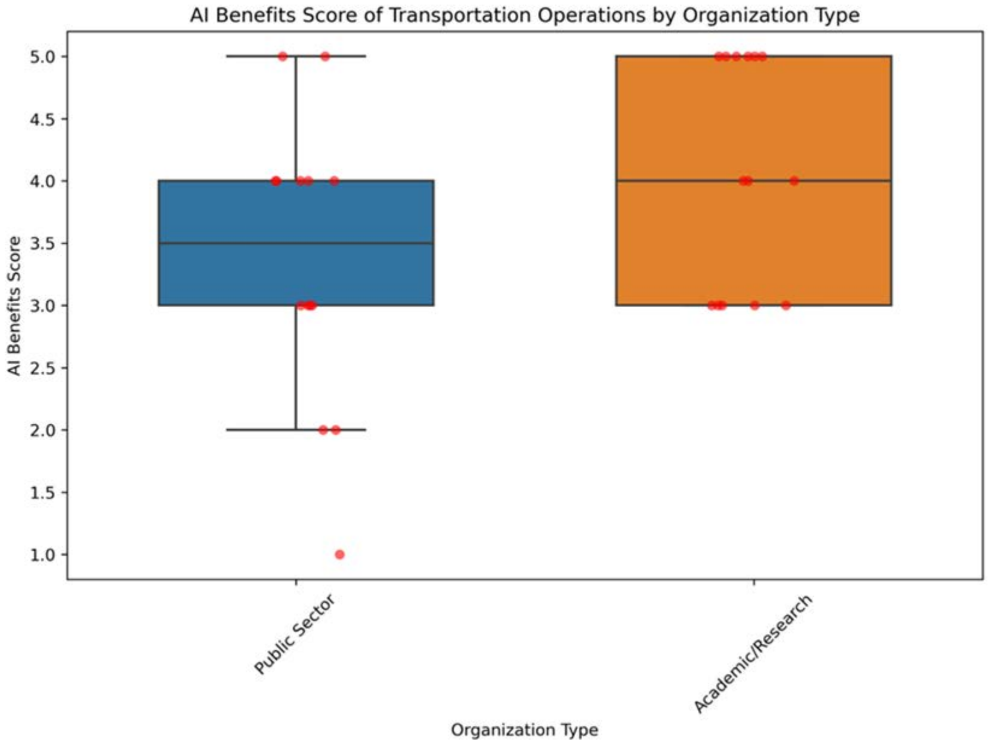
ANOVA Results: F=0.15, p=0.71, No significant difference

Figure D3 Differences of AI Benefits by Organization Type - Transportation Safety



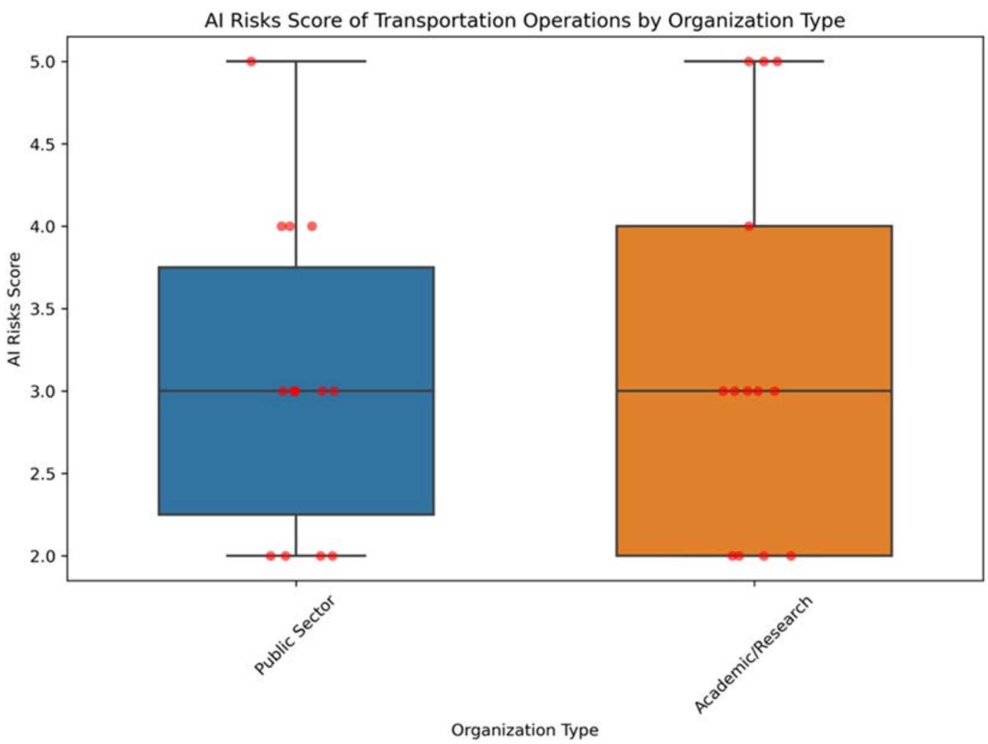
ANOVA Results: F=2.21, p=0.15, No significant difference

Figure D4 Differences of AI Risks by Organization Type - Transportation Safety



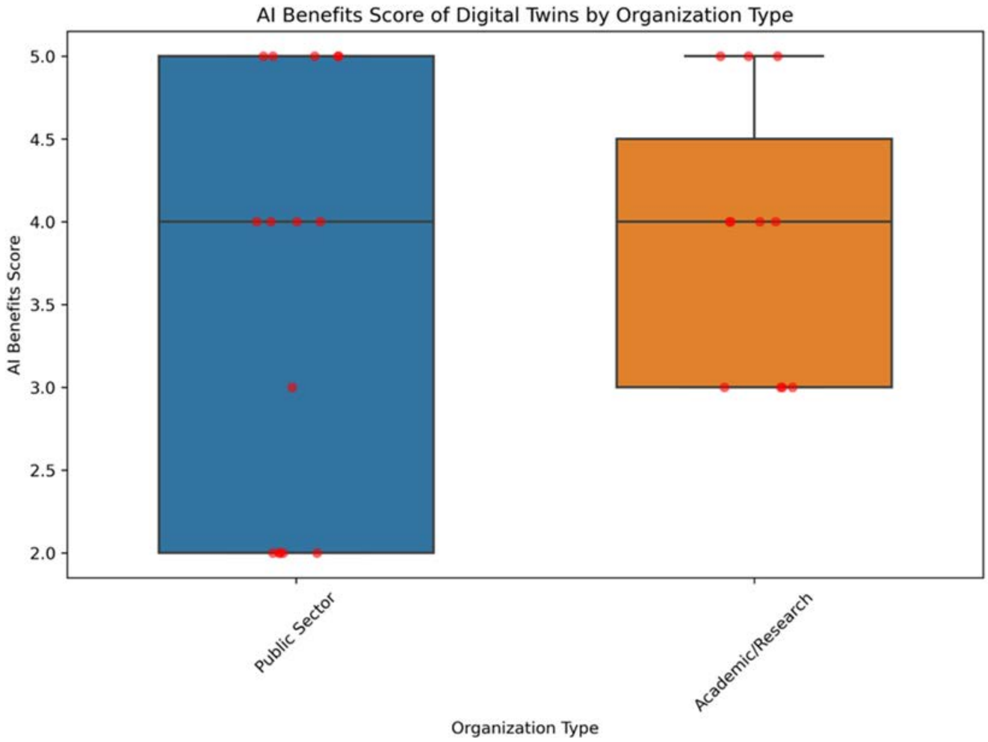
ANOVA Results: F=3.29, p=0.081, No significant difference

Figure D5 Differences of AI Benefits by Organization Type - Transportation Operations



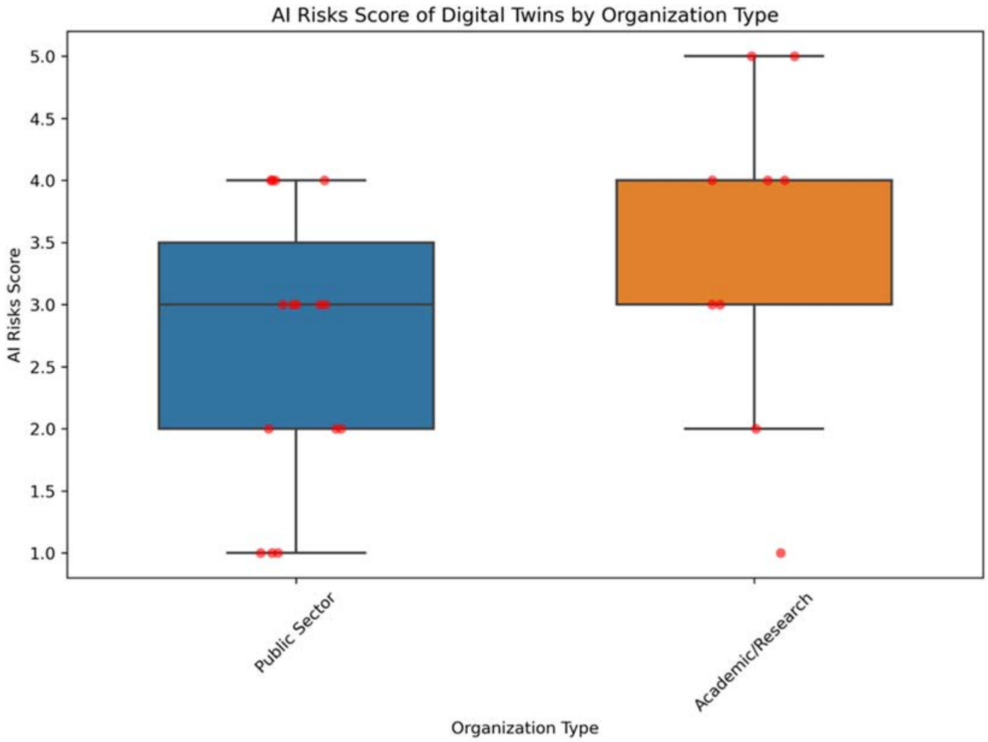
ANOVA Results: F=0.16, p=0.69, No significant difference

Figure D6 Differences of AI Risks by Organization Type - Transportation Operations



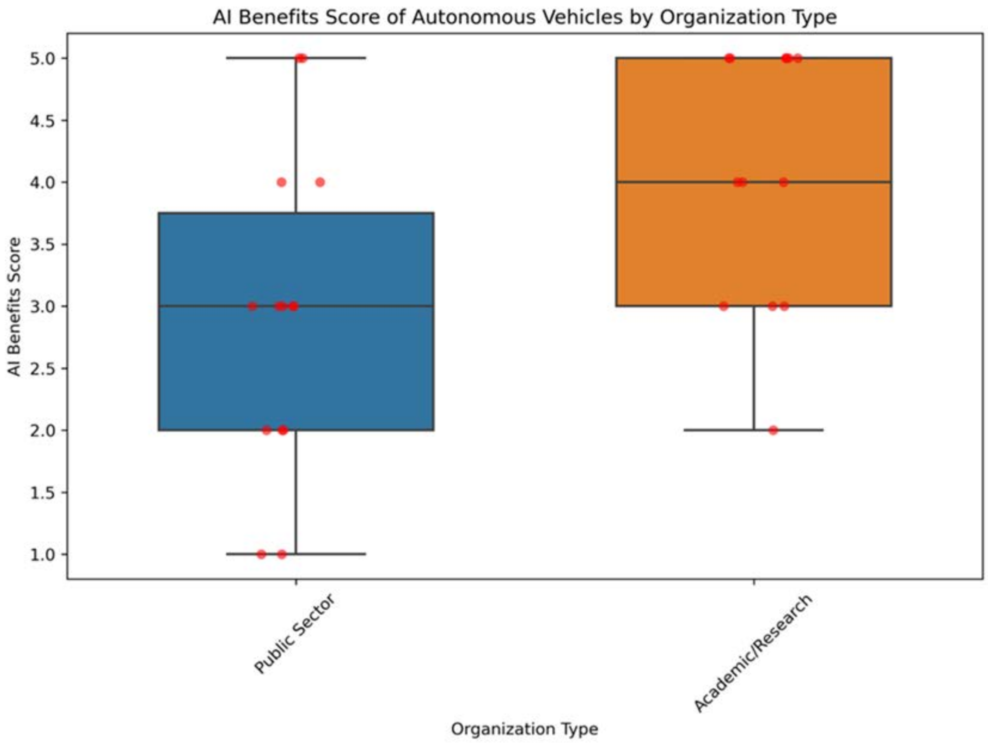
ANOVA Results: F=0.48, p=0.49, No significant difference

Figure D7 Differences of AI Benefits by Organization Type - Digital Twins



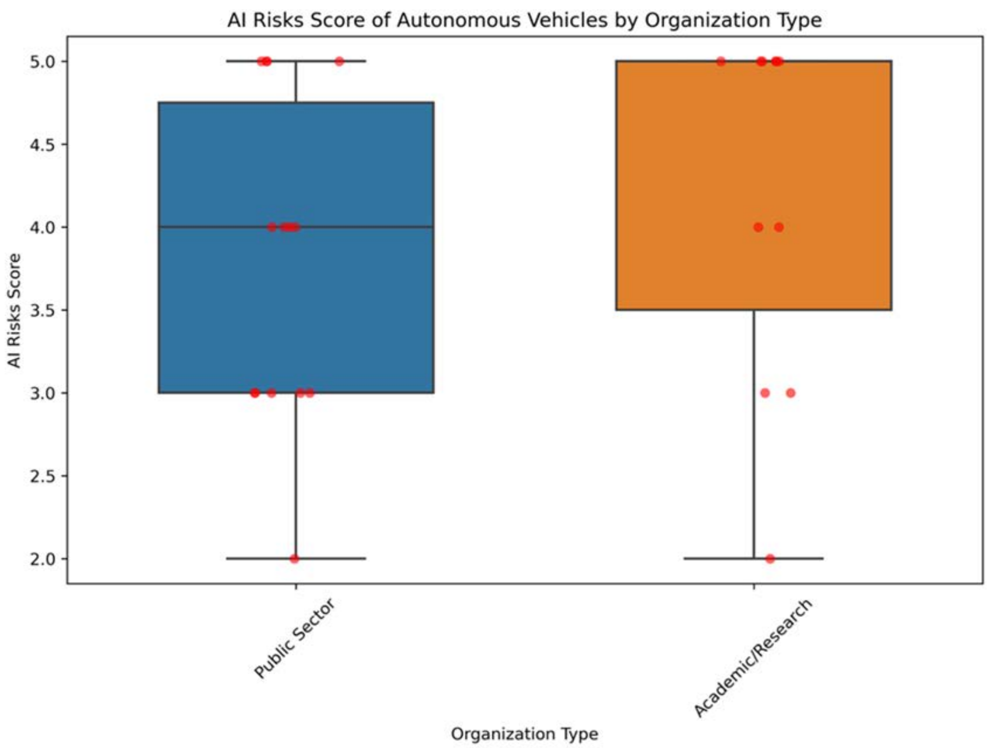
ANOVA Results: F=2.37, p=0.14, No significant difference

Figure D8 Differences of AI Risks by Organization Type - Digital Twins



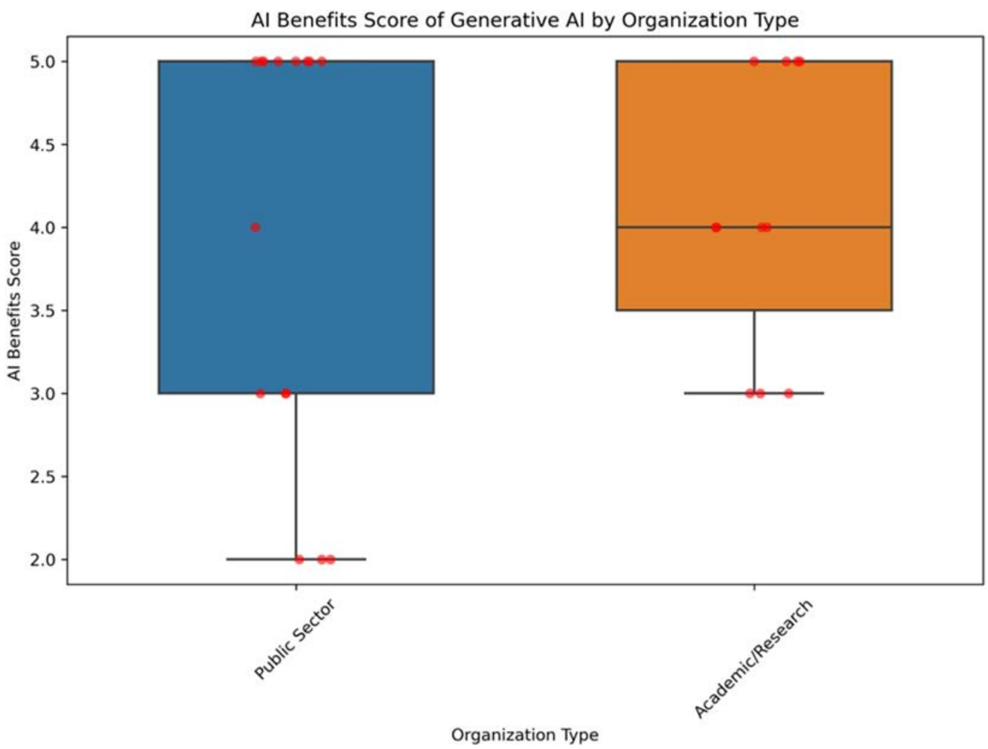
Tukey HSD test results: p=0.017, Significant difference

Figure D9 Differences of AI Benefits by Organization Type - Autonomous Vehicles



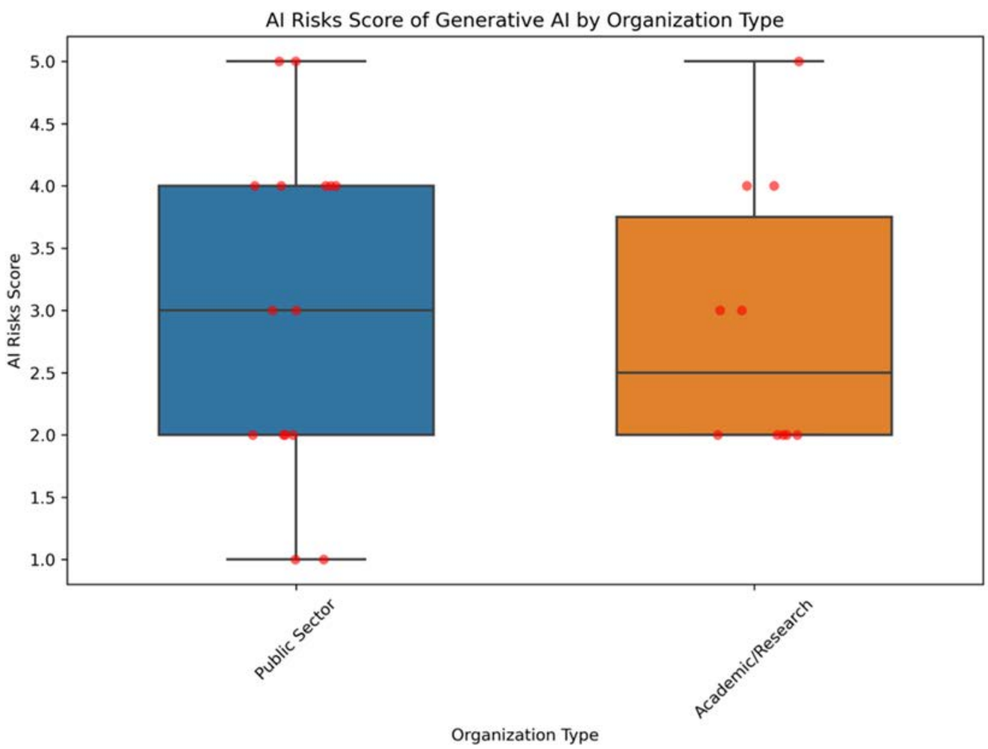
ANOVA Results: F=0.93, p=0.35, No significant difference

Figure D10 Differences of AI Risks by Organization Type - Autonomous Vehicles



ANOVA Results: F=0.13, p=0.72, No significant difference

Figure D11 Differences of AI Benefits by Organization Type - Generative AI



ANOVA Results: F=0.11, p=0.75, No significant difference

Figure D12 Differences of AI Risks by Organization Type - Generative AI