2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #51870

Integrating Artificial Intelligence into Transportation Engineering Education: A Review of Curricula and Training Programs in the U.S.

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Abstract

The rapid advancement of artificial intelligence (AI) is reshaping transportation engineering (TE), creating demand for a new generation of engineers who can integrate AI tools into the design, operation, and management of transportation systems. While universities and industry training providers have begun to explore AI applications in TE, there is limited understanding of the current state of AI-related education, the extent of adoption, and the directions of future development. This study addresses these gaps by conducting a structured review of TE curricula and training programs in the United States, with a focus on how AI concepts, methods, and skills are being introduced in institutions. A mixed-method research approach was designed to combine quantitative and qualitative analyses. First, a curriculum survey compiled a database of TE programs and courses using publicly available resources such as catalogs and syllabi, focusing on keywords including "AI," "machine learning," "data science," "autonomous vehicles," and "intelligent transportation systems (ITS)." Second, content analysis classified instructional approaches and themes, such as AI fundamentals, AI-enhanced traffic modeling and decision support for transportation planning. Finally, classification and correclation models were applied to categorize offerings, identify patterns, and forecast trends in AI-integrated TE education. This study is relevant to both academia and industry. For academic institutions, it provides evidence-based insights to inform curriculum design and strategic planning. For industry, it highlights professional development strategies aligned with evolving standards.

Introduction

Transportation engineering is a discipline focused on the planning, design, operation, and management of transportation systems that enable the movement of people and goods. Unlike narrowly defined infrastructure oriented fields, transportation engineering inherently adopts a systems perspective, integrating physical infrastructure, vehicles, users, information, and policy. It relies on methods such as traffic flow theory, demand modeling, simulation, optimization, safety analysis, and economic evaluation to support decision making across the life cycle of transportation systems. The field plays a critical role in addressing societal challenges such as congestion, safety, accessibility, sustainability, and equity, particularly in the context of growing urbanization and increasing mobility demands. Transportation systems are fundamentally socio technical, shaped not only by engineering design but also by human behavior, institutional constraints, and regulatory frameworks.

In recent years, rapid advances in artificial intelligence (AI) have begun to transform how transportation systems are analyzed, operated, and controlled [1]. AI techniques such as large language models, reinforcement learning, computer vision, and data driven optimization offer new capabilities for processing large scale mobility data, modeling complex travel behavior, and enabling adaptive and real time system control. Applications of AI in transportation engineering include traffic signal control, autonomous and connected vehicles, intelligent transportation systems, demand prediction, incident detection, and sustainable mobility planning [2]. These approaches allow transportation engineers to move beyond static and rule based methods toward more responsive and predictive system designs that can better handle uncertainty and dynamic conditions.

At the same time, transportation engineering provides an essential foundation for the responsible deployment of AI in mobility systems. AI driven transportation technologies will be integrated into existing infrastructure, evaluated for safety and reliability, and assessed for their impacts on efficiency, emissions, and social equity. Transportation engineers bring expertise in system modeling, performance evaluation, human factors, and policy analysis that is critical for translating AI innovations into deployable and trustworthy solutions. In this sense, AI based transportation systems are complex systems of systems that require rigorous engineering frameworks to ensure they function effectively in real world environments.

While the interaction between artificial intelligence and transportation engineering has been widely studied in research and practice [3], particularly in areas such as intelligent transportation systems and autonomous mobility, the integration of AI into transportation engineering education has received comparatively less attention. Preparing future transportation engineers requires curricula that combine foundational transportation theory with modern AI concepts and tools. Such integration is increasingly important as transportation professionals are expected to work with large datasets, adaptive control algorithms, and AI enabled decision support systems. Embedding AI into transportation engineering education offers an opportunity to better align academic training with the evolving needs of practice while fostering innovation in sustainable and intelligent mobility systems.

In this paper, we aim to address the following questions:

RQ1: How prevalent are AI related courses within transportation engineering education programs across U.S. universities?

RQ2: What transportation specific themes and AI techniques are emphasized in these courses?

RQ3: How might the integration of AI shape the future evolution of transportation engineering education?

Methodology

Data Search and Collection Methods

The objective of this research is to examine the current integration of artificial intelligence (AI) related content in transportation engineering education programs and to identify the challenges and feasibility associated with implementing AI focused coursework. To achieve this objective, we adopted the Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) protocol to guide the systematic review process. The PRISMA guidelines and flow diagram are widely used in systematic literature reviews [4] and provide a transparent and structured framework for identifying, screening, and selecting relevant records. Beyond their traditional application in literature reviews, the structured nature of the PRISMA methodology is also well suited for curriculum focused investigations. Accordingly, this framework was used to organize and document the data collection and screening procedures for transportation engineering curricula.

To collect curricular data, we first identified institutions offering transportation engineering education through civil engineering or closely related programs. Our search focused on universities recognized in the U.S. News Top 100 rankings for civil engineering programs. In addition, we examined ABET accredited civil engineering programs (100 programs) with formal transportation engineering tracks or concentrations. Data from the American Society for Engineering Education (ASEE) were also referenced to capture the breadth of undergraduate and graduate civil engineering offerings across the United States (50 institutions). Collectively, these sources provided a comprehensive overview of institutions actively engaged in transportation engineering education and training programs.

Next, we reviewed the course catalogs of the identified institutions to determine the extent to which AI related content is incorporated into transportation engineering curricula. For each institution, we collected information on course titles, course descriptions, program level (undergraduate or graduate), course types (core or elective), and, when publicly available, syllabi and instructional materials. Courses were classified as AI related if they included topics such as machine learning, data driven modeling, intelligent transportation systems, connected and automated vehicles, reinforcement learning, or advanced traffic analytics, etc. This process enabled a systematic assessment of both the prevalence of AI related courses and the thematic areas emphasized within transportation engineering education. The overall screening and selection process is summarized using a PRISMA flow diagram, as shown in Figure 1.

Prior to screening, 129 duplicate records were removed, resulting in 121 unique institutions entering the screening stage. During the screening phase, 30 records that did not provide specific transportation engineering programs. The remaining 91 records were subsequently assessed. At this stage, 58 records were excluded with specific reasons, such as absence of AI related content, or insufficient curricular information. Ultimately, 33 studies satisfied all eligibility criteria and were included in the final review.

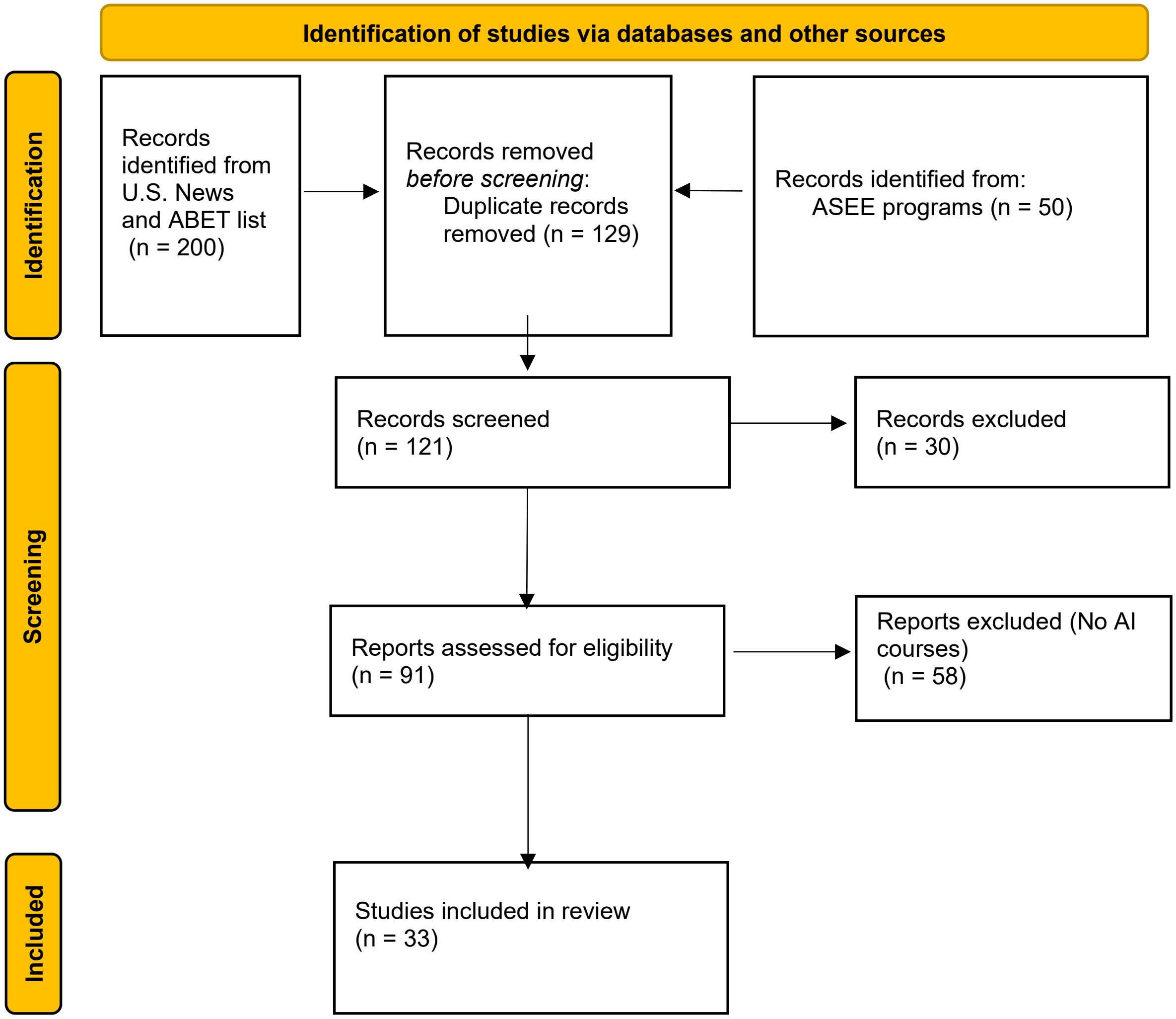

Figure 1. PRISMA Flow Diagram

Data Processing and Analysis Methods

The analysis is based on a structured curriculum dataset compiled from publicly available course information across U.S. universities offering transportation engineering related programs. The data were first preprocessed to ensure consistency, including the consolidation of repeated institutional entries and the standardization of course attributes such as course level and course type. The study primarily employs descriptive statistical analysis to summarize institutional participation, course characteristics, and curricular structure. Counts, proportions, and distributions were used to characterize the prevalence of AI related coursework across universities, degree levels, and course types.

To identify AI related content within transportation engineering curricula, a content based text screening approach was applied to course descriptions. Courses were classified as AI related if they contained an explicit course description that reflecting the presence of AI keywords aformentioned. In complementary analyses, keyword based text analysis was used to examine thematic patterns within course titles and descriptions, allowing for the identification of AI related concepts across programs. This approach aligns with commonly used methods in curriculum studies and educational data mining, where rule based text classification and dictionary based keyword matching are employed to infer topical coverage from course metadata.

Together, these methods provide a transparent and reproducible framework for assessing the current state of AI integration in transportation engineering education. The combination of descriptive statistics and rule based text analysis enables both quantitative comparison across institutions and qualitative insight into how AI content is positioned within academic curricula.

Results and Findings

The Levels, Types and Distribution of AI-courses across Universities

To answer RQ 1, we first examined the course levels (undergraduated/graduated or both) and course types (cores or electives) of AI related courses within transportation engineering programs across universities in Figure 2.

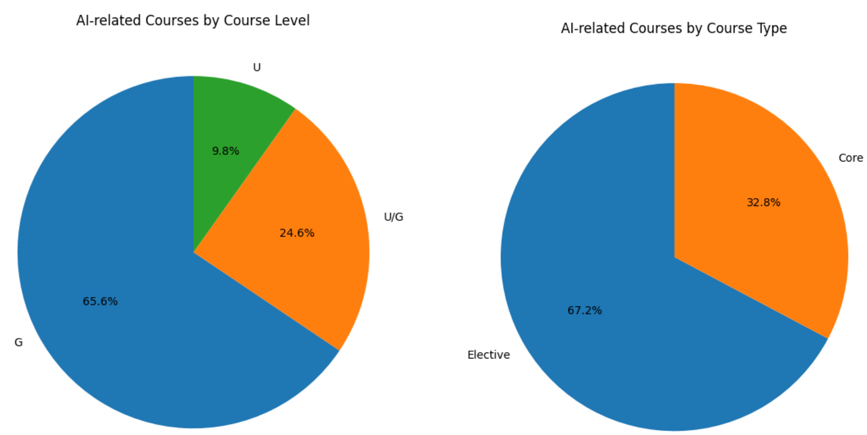

Figure 2. AI-related Courses by Level and Type

Graduate level courses account for 65.6% of all identified offerings, while undergraduate only courses represent a much smaller share for 9.8%, with an additional portion serving both undergraduate and graduate students (24.6%). This pattern indicates that AI is largely positioned as an advanced topic, with relatively limited integration into undergraduate transportation engineering education. A majority of courses (67.2%) are offered as electives, whereas only 32.8% are designated as core requirements. This imbalance suggests that formal exposure to AI in transportation engineering often depends on student choice rather than being embedded as a program wide requirement.

We then presents the distribution of AI related courses across universities.

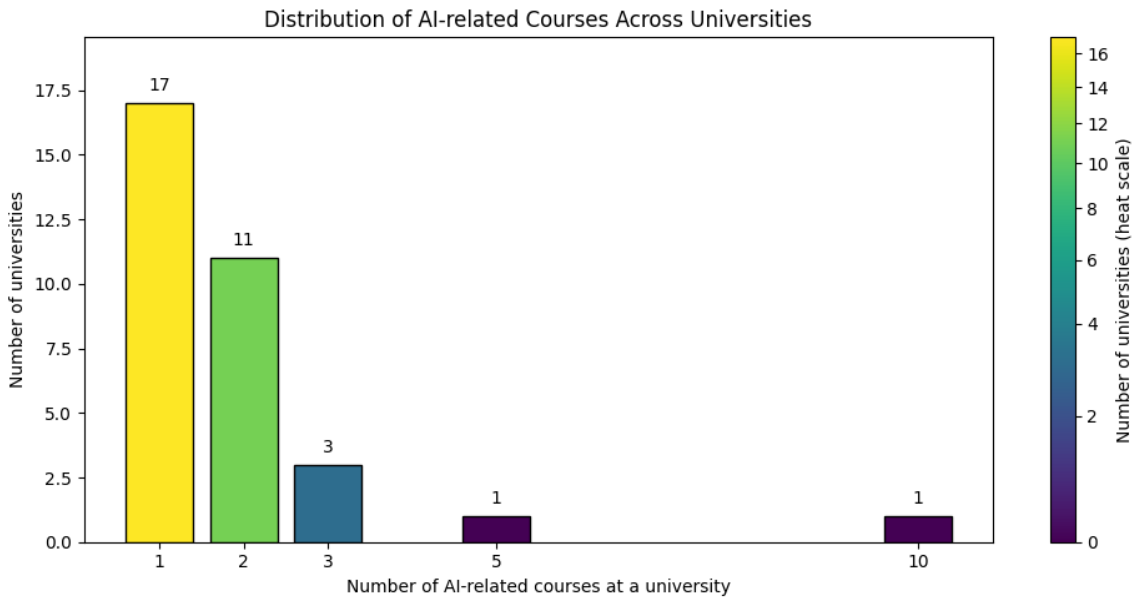

Figure 3. Distribution of AI Courses across Universities

Most institutions that include AI related content offer only a single such course, with fewer universities providing two or three courses and only a small number offering a more extensive portfolio of AI focused transportation courses. In many cases, universities offering only one AI related course primarily introduce general concepts of artificial intelligence for civil or transportation engineering students. Institutions offering two AI related courses tend to expand this exposure by incorporating data science or analytics oriented content. In contrast, the few universities that offer more than five AI related courses typically provide structured AI curricula designed specifically for engineering students. This skewed distribution indicates that AI integration within transportation engineering programs is generally shallow and fragmented, with substantial variation across institutions. Collectively, these findings highlight the absence of a consistent and structured approach to AI education in transportation engineering programs nationwide.

AI-topic Distributions of Courses

To further examine how artificial intelligence is represented within transportation engineering curricula, we analyzed course descriptions using a keyword-based content analysis approach to answer RQ 2. This analysis focuses on identifying dominant AI topic categories and the specific concepts emphasized across courses. By examining the distribution of AI topics, we provide insight into not only the presence of AI in transportation engineering education, but also the substantive areas in which AI training is concentrated.

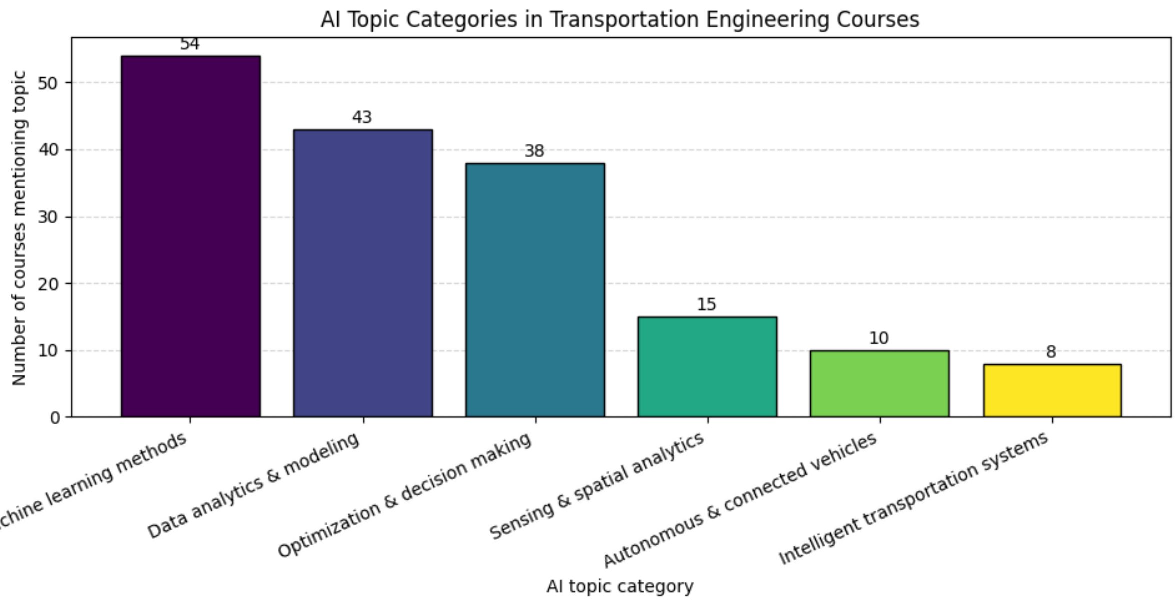

Figure 4. AI Topic Categories in Course Descriptions

These topics appeared in all the course descriptions, which we should point out that one course may include several topics at a time. For example, one course can include both machine learning methods and data analysis key words. The detailed keywords for each topic category is given in Table 1.

Table 1. Representative Keywords among Courses

AI Topic Category	**Representative Keywords**	**Number of Courses**
Machine learning methods	machine learning, artificial intelligence, deep learning, neural networks, supervised and unsupervised learning, classification, reinforcement learning, llm	54
Data analytics & modeling	data, analytics, prediction, forecasting, regression	43
Optimization & decision making	optimization, control, decision making, scheduling, Bayesian methods, modeling	38
Sensing & spatial analytics	spatial analysis, sensors, sensing, computer vision, GIS	15
Autonomous & connected vehicles	autonomous vehicles, connected vehicles, automation, V2X	10
Intelligent transportation systems	intelligent transportation systems, traffic control, traffic management	8

To take a closer look at the AI topic categories, the keyword-based analysis of course descriptions reveals clear differences in emphasis across thematic areas. As shown in Table 1, machine learning methods and data analytics and modeling are the most prevalent categories, appearing in 54 and 43 courses, respectively, indicating that AI instruction in transportation engineering is largely centered on data-driven and learning-based approaches. Topics related to optimization and decision making also appear frequently, suggesting a strong focus on algorithmic decision support and control. In contrast, application-oriented areas such as sensing and spatial analytics, autonomous and connected vehicles, and intelligent transportation systems are referenced far less often. This imbalance indicates that, while foundational AI techniques are increasingly incorporated into transportation engineering education, advanced and system-level AI applications remain limited and unevenly represented across curricula.

AI-keywords Correlation among Courses

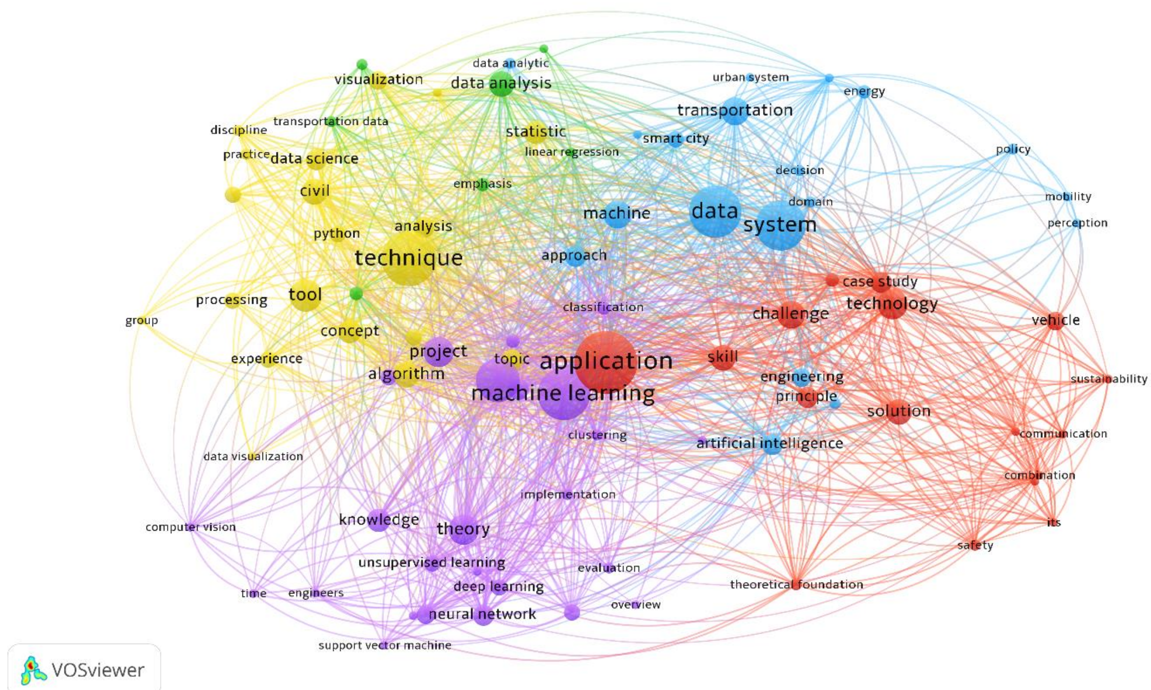

Figure 5. Correlation among Keywords in Description

To further answer RQ 2, Figure 5 presents a keyword co-occurrence network generated using VOSviewer, where node size represents keyword frequency, link thickness reflects co-occurrence strength, and colors indicate clusters of closely related concepts. The visualization reveals a structured landscape centered on AI and transportation engineering, with strong interdisciplinary connections across transportation domains, machine learning, and data sciences. Below is the interpretation of each cluster.

Table 2. Cluster Correlation Analysis

Purple cluster (lower left): machine learning and algorithm foundations	This cluster groups keywords such as machine learning, algorithm, neural network, deep learning, unsupervised learning, and support vector machine. It represents the methodological backbone of the field, focusing on learning paradigms, model architectures, and theoretical considerations. The strong links between this cluster and the central application node indicate that algorithm development is closely motivated by real world problem solving rather than purely theoretical exploration.This reflects the current course offering AI content towards use real-world problem rather than focusing modeling itself.
Blue cluster (upper right): data-driven systems and transportation context	Keywords including data, system, transportation, smart city, urban system, decision, and policy form a cohesive cluster emphasizing system level integration. This cluster highlights the role of data driven decision making within transportation and urban environments. Its strong connectivity to both machine learning and application technology suggests that data-driven system design serves as a bridge between advanced analytics and operational deployment in smart cities.
Red cluster (lower right): Engineering applications and technological solutions	This cluster contains terms such as technology, engineering, solution, vehicle, ITS, sustainability, and safety. This group reflects applied engineering concerns and domain specific implementations. The presence of case study and challenge indicates that this emphasizes validation, deployment constraints, and real world performance, reinforcing the practical orientation of this area.
Yellow cluster (upper left): Analytical techniques and practical tools	This cluster is characterized by technique, analysis, tool, python, data science, and processing. It represents the applied analytical skill set required to operationalize machine learning models. Its proximity to both algorithmic and application focused clusters suggests that computational tools and data analysis techniques play a critical enabling role rather than being standalone contributions.
Green cluster (upper middle): Statistical analysis and visualization	Keywords such as data analysis, statistics, linear regression, visualization, and transportation data define this cluster. It reflects the continued importance of classical statistical methods and exploratory analysis, particularly in interpreting complex transportation datasets and supporting model evaluation.

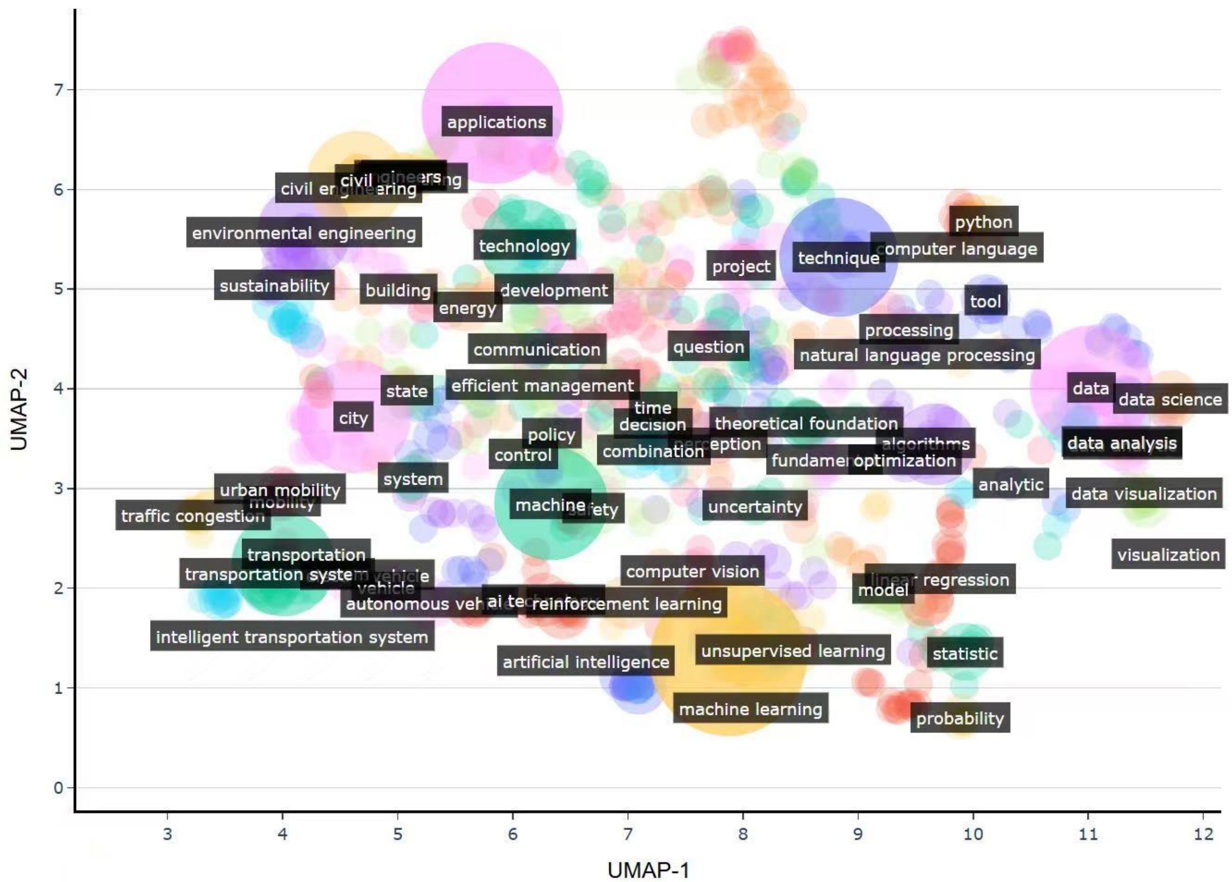

Figure 6. Uniform Manifold Approximation and Projection (UMAP) Analysis

Figure 6 illustrates a two dimensional UMAP projection of keyword embeddings extracted from the course description related to artificial intelligence and transportation engineering education. Each node represents a keyword, where node size reflects the relative frequency or prominence of the keyword, and spatial proximity indicates semantic similarity based on embedding distance. Keywords that appear closer together tend to co-occur in similar educational or research contexts, while those farther apart reflect more distinct conceptual roles.

The extensive overlap between clusters suggests that current curricula integrate machine learning, where students simultaneously engage with data, models, and transportation contexts. This integration aligns with the growing demand for graduates who can not only develop AI models but also interpret results, understand system impacts, and translate technical insights into engineering and policy decisions. Moreover, the prominence of transportation specific keywords alongside general AI concepts indicates that the field has moved beyond generic AI instruction toward domain tailored AI education. RQ 3 should be answered by referring to this analysis.

Discussion

The findings of this study suggest that transportation engineering education in the United States is currently undergoing a gradual but uneven transition toward the integration of artificial intelligence. While AI-related content is increasingly visible across university curricula, only a small number of institutions offer a substantial portfolio of AI-focused courses. For the majority of programs, AI appears primarily at an introductory level, often limited to a single course or a small set of electives. This pattern indicates that AI has not yet been fully embedded as a core component of transportation engineering education, but rather introduced as an emerging topic that supplements traditional curricula, this trend also noted in prior studies on AI-integrated engineering education[5],[6].

At the same time, the results reveal a clear shift in educational priorities among transportation engineering educators. There is growing recognition of the importance of AI and data-driven methods, which is reflected in the increasing inclusion of computer science–oriented AI and data analytics courses as electives within transportation programs. Rather than developing entirely new, transportation-specific AI courses, many programs appear to rely on existing courses in machine learning, data science, or analytics, often housed in computer science or engineering departments. This approach aligns with broader trends in engineering education, where interdisciplinary borrowing is commonly used to respond to rapidly evolving technologies[7].

Beyond traditional academic programs, this trend is also evident in professional training and continuing education offered by external organizations. Transportation agencies and research organizations have begun to incorporate AI-focused training into their workforce development efforts, either in collaboration with universities or through independent initiatives. For example, the Washington State Department of Transportation has supported AI- and data-oriented research and training activities in collaboration with the University of Washington and Washington State University, particularly in areas related to intelligent transportation systems and data analytics [8],[9]. Similarly, professional organizations such as ITS America have expanded their educational offerings to include workshops, webinars, and short courses focused on artificial intelligence, automation, and data-driven transportation solutions [10]. These developments indicate that demand for AI-related skills is being driven not solely by academic innovation but also by workforce and policy needs.

Despite this momentum, the appropriate direction and depth of AI integration in transportation engineering education remain open questions. Not all students entering transportation engineering programs seek intensive training in computer science, advanced coding, or AI model development [11]. For students pursuing careers in planning, policy, operations, or management, highly technical AI coursework may be less relevant than applied analytical tools or conceptual understanding of AI-enabled systems. Prior research in engineering education suggests that misalignment between curricular content and student career pathways can reduce engagement and learning outcomes [12]. As a result, the expansion of AI content should be guided by careful assessment of labor market needs, student goals, and the diverse roles transportation engineers play in practice.

Taken together, these findings highlight the need for a more deliberate and balanced approach to AI integration in transportation engineering education. Rather than adopting a one-size-fits-all model, programs may benefit from tiered curricular structures that distinguish between AI literacy, applied AI tools for transportation practice, and advanced AI development for research-oriented students. Such an approach would allow transportation engineering programs to respond to technological change while remaining inclusive of diverse student interests and aligned with evolving industry demands.

Conclusion and Future Research

This study provides a systematic, data-driven examination of the thematic structure of artificial intelligence within transportation engineering education. The analysis shows that artificial intelligence are central organizing elements, but they are not treated as standalone technical subjects. Instead, they are tightly integrated with transportation applications, system level concepts, and data oriented skills. Both visualizations consistently reveal applications as a dominant theme, indicating that AI education in transportation engineering is primarily driven by practical problem solving rather than purely theoretical development. The analysis also indicates that, although AI content is increasingly present across transportation engineering programs, the overall depth of AI focused coursework remains limited at many universities. Most offerings emphasize introductory concepts and applied exposure rather than advanced technical depth. Nevertheless, the consistent inclusion of AI topics reflects a clear upward trend, suggesting that continued experimentation with AI course design is both timely and worthwhile.

While this study offers a comprehensive overview of the current structure of AI in transportation engineering education, several avenues for future research remain. First, future studies may extend the analysis to include temporal evolution, examining how AI related educational themes have changed over times. Second, future research may explore pedagogical effectiveness, connecting topic structures with student learning outcomes, industry readiness, and workforce demands. Finally, expanding the scope to include cross disciplinary comparisons with other engineering fields may provide insights into best practices for AI education and identify opportunities for shared instructional frameworks.

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