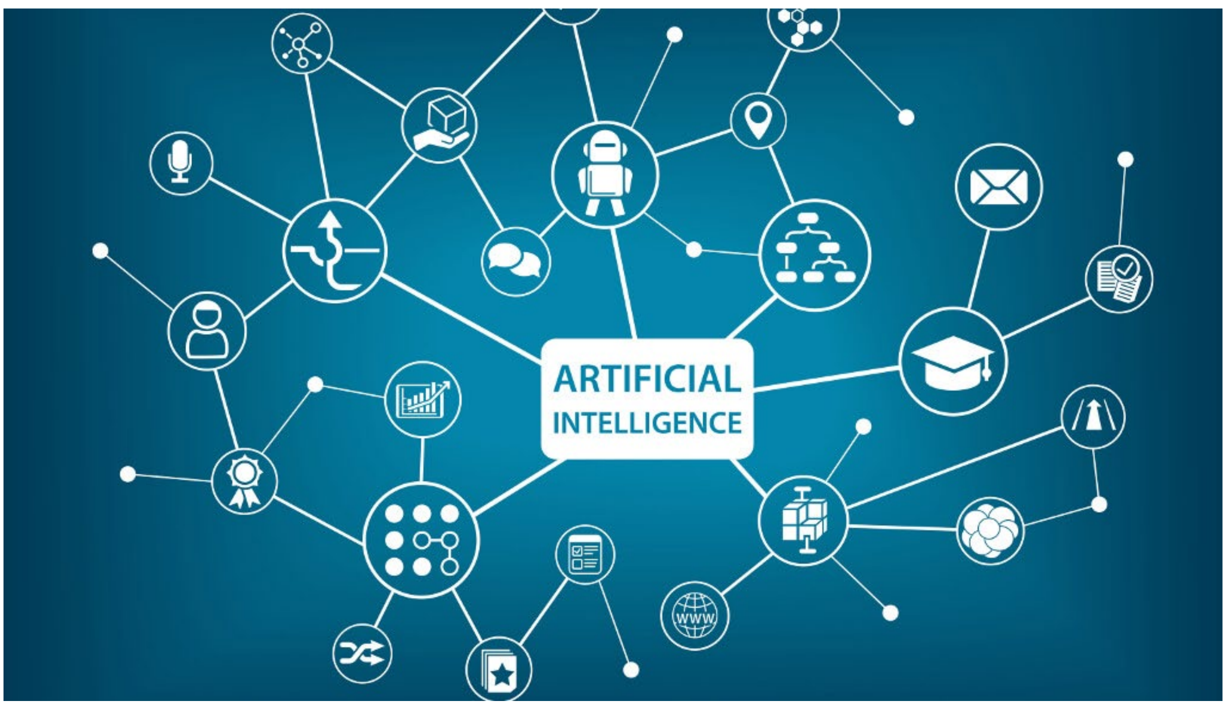
Raising Awareness of Artificial Intelligence for Transportation Systems Management and Operations

Final Report

December 2019



U.S. Department of Transportation
Federal Highway Administration

FOREWORD

The Federal Highway Administration (FHWA) Office of Operations (HOP) is pleased to present this report on the fundamentals of Artificial Intelligence (AI) technologies and potential areas of AI applications in Transportation Management Center (TMC) operations.

This publication's status is: final.

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16. Abstract

This report introduces the fundamentals of Artificial Intelligence (AI) technologies and potential areas of AI applications in Transportation Management Center (TMC) operations; documents successful AI applications and lessons learned in TMC operations; showcases TMCs using AI to improve their operations; and identifies needs for future studies on this topic. The report provides guidance to assist transportation agencies with better preparation for the potential impacts of AI on operational activities, resources, system needs, and decisionmaking.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ACRONYMS

3D	Three Dimensional
AI	Artificial Intelligence
aaS	As a Service
API	Application Programming Interfaces
ATM	Active Traffic Management
AWS	Amazon Web Services
BI	Business Intelligence
BVLOS	Beyond Visual Line of Sight
Caltrans	California Department of Transportation
CCTV	Closed-Circuit Television
DelDOT	Delaware Department of Transportation
DOT	Department of Transportation
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GIS	Geographic Information Systems
I2V	Infrastructure to Vehicle
IaaS	Infrastructure as a Service
IOO	Infrastructure Owners and Operators
IVR	Interactive Voice Response
LiDAR	Light Detection and Ranging
MTC	Metropolitan Transportation Commission
NCDOT	North Carolina Department of Transportation
NDOT	Nevada Department of Transportation
NLP	Natural Language Processing
NoSQL	Not Only SQL
OCR	Optical Character Recognition
ONNX	Open Neural Network Exchange
PaaS	Platform as a Service
QA	Question-Answering
SaaS	Software as a Service
SQL	Structured Query Language
SWARM	System-Wide Automatic Ramp Metering
TIMELI	Traffic Incident Management Enabled by Large-data Innovations
TMS	Transportation Management System
TSMO	Transportation Systems Management and Operations
UAS	Unmanned Aerial Systems
V2I	Vehicle to Infrastructure
VDOT	Virginia Department of Transportation
WSDOT	Washington State Department of Transportation

EXECUTIVE SUMMARY

This report introduces the fundamentals of artificial intelligence (AI) technologies and the potential applications in transportation management system (TMS) and transportation management center (TMC) operations, showcases successful AI applications for TMSs, and provides a list of important issues to consider in developing AI applications. This information is intended to raise the awareness of transportation agencies of the potential benefits, implications, and impacts of using AI for a TMS, TMC operations, or a transportation systems management and operations (TSMO) program.

AI and machine learning are elements of business intelligence (BI) strategies and technologies, which are used by enterprises for data analysis and information extraction. Traditional problems, functions, or actions that AI techniques can address include reasoning, knowledge representation, planning, learning, natural language processing (and understanding), perception, and the ability to move and manipulate objects.[1] In each problem area, AI technologies are proving to have significant performance benefits versus other traditional mathematical modeling approaches. For example, the capabilities of Alexa and Google Assistant to understand human speech significantly outperforms the interactive voice response (IVR) technologies used in 511 systems over the past 20 years.

Colloquially, "artificial intelligence" typically describes the ability of a machine to mimic human actions or cognitive functions, such as problem solving or maintaining a conversation. This type of artificial intelligence is typically referred to as ***"strong" AI.*** There are no strong AI systems in existence. Other specialized applications of AI are termed ***"weak" AI*** or ***machine learning applications.*** Machine learning applications offer the potential to supplant human work in a variety of TSMO areas, including traffic imagery analysis, incident detection, traffic control and traffic signal timing, TMC function automation, and data analysis.

Chatbots and question-answering (QA) systems may enable new ways to obtain insights in data. Neural networks can analyze imagery from a variety of sources for incident detection, incident management, and traffic data collection. Fuzzy logic is already used by a variety of departments of transportation (DOT) for ramp metering and fuzzy logic may find additional applications by simplifying *if…then* rule bases for decision-support systems. Unsupervised AI systems may learn new ways to control traffic and coordinate integrated corridor management actions across a variety of control and advisory technologies. Driverless vehicles and airborne and ground-based unmanned aerial systems (UAS) may improve TSMO staff safety and productivity. Additional applications may arise as agencies gain experience with AI tools and technologies.

There are thousands of companies competing for dollars in the AI space across essentially every consumer and Government market as the technology continues to mature. Technologies from Google, Amazon, Microsoft, and Facebook and open-source tools they have either developed or adopted tend to underpin most software and hardware AI products. As with Big Data a few years ago, hype in the capabilities of AI is also at a peak. As time moves on, these technologies are

1 https://en.wikipedia.org/wiki/Artificial_intelligence

likely to come closer and closer to "plug and play," but currently there is still a reasonably large barrier between the dreams of AI-enabled TSMO applications and the need for significant expertise and investment to make those dreams a reality. As fast as the pace of development of AI tools and technologies is progressing, AI applications should find their way from research experiments and pilot demonstrations to fully scalable applications in the near term.

Common trends in AI development over the next five years, according to Forbes, may be:[2]

- Development of AI-specific hardware chips for embedding machine learning and training in consumer products, industrial processes, and vehicles.
- Movement of machine learning models from centralized Cloud systems to edge Internet of Things (IoT) devices.
- Interoperability among neural network modeling systems and frameworks via Open Neural Network Exchange (ONNX).[3]
- Automated machine learning with AutoML—speeding the process of building and deploying neural networks.
- Application of AI analysis to information technology operations.
- Continued evolution of chatbots and virtual assistants into more comprehensive, context-sensitive question and answer functions.
- Deployment of consumer-ready automated vehicle services.
- Democratization of machine learning services and software to professionals without deep software development and database management skills.
- Improvement of AI responsibility, transparency, and morality; the removal of systematic biases against minorities.

In the field of digital video processing, since existing products have already emerged for TSMO, the pace may be faster. Driverless vehicles are likely to be available to TSMO agencies in the near term and beyond visual line of sight (BVLOS)-automated unmanned aerial systems (UAS) operations in the medium term.

A variety of AI technologies have been deployed for TSMO applications. Several State and local DOTs (Nevada, Florida, and Iowa) have begun deploying neural network technologies for incident detection using video image analysis and traffic prediction. Fuzzy logic has been used by Washington State DOT for more than 20 years and California DOT (Caltrans) has begun deployment of fuzzy logic metering in a pilot corridor. Delaware DOT has piloted several AI applications for traffic congestion and incident prediction. The Metropolitan Transportation Commission of the Bay Area and several other agencies have light integration of 511 with Alexa. Several arterial management agencies are piloting use of Google Assistant. More than 20 State DOTs have active UAS programs that may be enhanced with AI in the near to medium term. Several DOTs are piloting use of automated vehicles for crash abatement. As AI technology continues to mature, the applications for AI in TSMO are likely to continue to expand.

2 https://www.forbes.com/sites/janakirammsv/2018/12/09/5-artificial-intelligence-trends-to-watch-out-for-in-2019/#36206b356183

3 https://onnx.ai/

Determining how to start in AI applications for TSMO will be unique to your organization. As is true with any TSMO activity, the basis for improvement of any activity with AI has three basic components:

1. A supporting institutional framework, policies, and appetite.
2. Processes, staff, and technology that support the program.
3. The implementation of the system itself.

The foundation of any successful program is first the institutional framework to support the activity. In the context of AI applications, developing the necessary organizational structure and functions for TSMO is an important element. After these enabling actions, the business processes for using AI technologies for TSMO practices should follow more readily and be more effective due to a strong foundation in business processes. These processes should enable the AI programs to function at a high level initially and continue to adapt and improve as AI technology advances.

Developing these foundational elements is important and answering the questions in chapter 5 will help to identify where the strengths and weaknesses lie. It is important to keep in mind in any technology deployment that some of the dimensions are inherently more difficult to deal with than others, yet they all should be addressed to move forward. Failing to consider issues related to staffing and organization, for example, may result in your AI project being a pilot that is never integrated into the main TSMO operation.

A holistic program plan may be developed considering many potential applications and pared back to consider what might be accomplished with more realistic budgets and resources. Agencies in the early planning stages may take the following steps:

1. Convene an interdepartmental workshop to educate stakeholders, partners, and potential partners on AI and brainstorm potential applications and synergies.
2. Discuss priorities, opportunities, and barriers to AI applications in each of the TSMO areas.
3. Determine a short list of high-priority applications and a longer list of secondary-priority functions that address regional issues, challenges, and goals. While many goals are generic, tailoring the AI strategy to regional hot-button issues is typically helpful in gaining broader buy-in from decisionmakers and associated departments of State DOTs and local infrastructure owner-operators (IOO).
4. Review the list of general and detailed questions in this chapter and consider the responses of your organization to each.
5. Develop a project plan to implement the actions.

CHAPTER 1. INTRODUCTION AND BACKGROUND

This report introduces the fundamentals of artificial intelligence (AI) technologies and the potential applications in transportation management system (TMS) and transportation management center (TMC) operations, showcases successful AI applications, and provides a list of important issues to consider in developing AI applications. This information is intended to raise the awareness of transportation agencies of the potential benefits, implications, and impacts of using AI for a TMS, TMC operations, or a transportation systems management and operations (TSMO) program.

The intended audience for this report is staff involved with TSMO programs and TMSs that are exploring how new and emerging technologies and methods could be utilized. After reading this report, you will have an awareness of the AI technologies which may or may not be applicable to specific TSMO programs and TMSs.

Possible impacts of AI on TSMO programs and TMS operations could include:

- Ramp metering.
- Coordinating the operation of traffic signals.
- Detecting incidents.
- Analyzing traffic images and videos.
- Managing and operating unmanned aerial systems (UAS) for traffic monitoring.
- Natural language decision support (Google assistant, Amazon Web Services (AWS) Alexa, Cortana) for traveler information and TMC operations.
- Automating fleet operations (e.g., crash abatement vehicles).
- UAS inspection of planned and unplanned incidents.
- Analysis of data from different sources and formats (e.g., emerging sources, such as connected vehicles).

The second chapter of this report briefly discusses the categories of AI. This discussion includes technologies such as neural networks, supervised and unsupervised machine learning, fuzzy logic, chatbots, robotics, and driverless air and ground vehicles. The third chapter discusses commercial AI products, suites of products available from service providers, how these technologies may differ, and issues agencies may consider when evaluating and possibly selecting these technologies. This chapter will raise your awareness of such tools and technologies and how they might be used to meet specific needs.

The fourth chapter highlights examples of AI applications being used to support TSMO programs and TMSs. This chapter focuses on incident detection, traffic prediction, digital assistants, and UASs. The fifth chapter identifies issues for TSMO agencies to consider when evaluating different AI technologies that may be applicable for a specific application.

After reading this report, you will be able to:

- Understand the basic types of AI technologies.
- Differentiate between supervised and unsupervised machine learning.
- Identify possible uses of AI in TSMO programs and TMSs.
- Identify the potential benefits of choosing one AI technology and comparing it to how an existing task, activity, or function is being performed, and suggest actions that your organization may need to take to incorporate AI technologies into your TSMO program activities.

CHAPTER 2. CATEGORIES OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES

INTRODUCTION

Transportation systems infrastructure owners and operators (IOO) are responsible for the planning, design, implementation, operation, and maintenance of the Nation's transportation assets. Transportation systems management and operations (TSMO) activities are frequently associated with transportation management centers (TMC).

Various TSMO programmatic areas, functions, or services within IOOs have varying degrees of sophistication in how they use *analytics* and *data* to support agency decisions. For example, pavement management programs and metropolitan planning processes within most departments of transportation (DOT) have a deep and extensive history in data-driven decisionmaking. Other programs, such as TSMO, are typically more ad-hoc in their use of data and analytics to inform key decisions. The use of performance measures, evaluating and reporting on performance, and data-driven decisionmaking processes and systems are gaining in popularity throughout IOOs.

Artificial intelligence (AI) and machine learning are elements of business intelligence (BI) strategies and technologies, which are used by enterprises for data analysis and information extraction. Traditional problems, functions, or actions that AI techniques can address include reasoning, knowledge representation, planning, learning, natural language processing (and understanding), perception, and the ability to move and manipulate objects.[4] In each problem area, AI technologies are proving to have significant performance benefits versus other traditional mathematical modeling approaches. For example, speech recognition systems in modern digital assistants are rapidly showing improved performance over interactive voice response (IVR) technologies used in 511 systems over the past 20 years.

Various types of AI technologies can be used to help IOOs for TSMO. For example, neural networks may help agencies improve incident detection time, fuzzy logic may simplify the configuration of ramp metering systems, and natural language question-and-answering systems may expand the abilities of TSMO staff to quickly obtain information from databases of facts and figures. This document provides an overview of past research, development, and capabilities of different AI technologies. This information will also identify what may be unique for each technology, what may be a limitation, and what issues to consider when evaluating if the technology will support the needs of the agency.

In this chapter, you will become aware of:

- The distinction between "strong" and "weak" AI.
- The subcategories of "weak" AI and the basic theory of each.
- The differences between supervised and unsupervised learning.
- "Weak" AI that is relevant to various TSMO functions.

[4] https://en.wikipedia.org/wiki/Artificial_intelligence

Over the last 60 years, AI research and development funding and interest has waxed and waned as the power of computers, programming languages, databases, search algorithms, and related technologies has developed. With each advancement in technology, developers are routinely optimistic about the potential for computers to replace humans in doing a wide variety of work tasks. In the early 1960s, AI funding from the U.S. and other Government agencies was substantial and the optimism that artificial intelligence would supplant many aspects of human work was substantial. When progress slowed and grandiose claims went unrealized, an "*AI winter*" lasted until the 1980s when computing power, memory, and database capabilities began to catch up with the dreams of AI developers.[5]

Colloquially, "artificial intelligence" typically describes the ability of a machine to mimic human actions or cognitive functions, such as problem solving or maintaining a conversation. This type of artificial intelligence is typically referred to as ***"strong" AI.*** There are no strong AI systems in existence, although progress will remain steady as digital assistants (Google Assistant, Facebook DrQA, Amazon Alexa, etc.) will continue to increase in capability to mimic what strong AI represents. Other specialized applications of AI are termed ***"weak" AI*** or ***machine learning applications.*** Machine learning applications offer the potential to supplant human work in a variety of TSMO areas, including traffic imagery analysis, incident detection, traffic control and traffic signal timing, TMC function automation, and data analysis.

GENERAL CATEGORIES OF MACHINE LEARNING

Chatbots, Computational Linguistics, and Question-Answering Systems

Chatbots are AI systems that can respond to questions from a human as shown in figure 1. Until the invention of Amazon Alexa and Google Assistant, historically, chatbot interaction was through a text interface. Over the years, chatbot technology has evolved significantly, and some chatbot developers have claimed they can pass the Turing Test.[6,7] The Turing Test is the most famous test of strong AI competency, named after the mathematician Alan Turing. Turing's hypothesis states that if a human person could not distinguish responses in a general conversation from a computer or a person, then the artificial entity would be considered "intelligent." In practice, chatbots are only able to "pass" the Turing test in limited situations (e.g., customer service phone calls) for a limited amount of time with assumptions about the bot's command of language, breadth of education (age), and subject knowledge (e.g., history, physics),[8] and the interrogator can only ask questions that are generally in the area in which the bot is expected to know some context.

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5 https://en.wikipedia.org/wiki/AI_winter
6 https://www.extremetech.com/computing/269030-did-google-duplexs-ai-demonstration-just-pass-the-turing-test
7 https://www.scottaaronson.com/blog/?p=1858
8 https://www.bbc.com/news/technology-27762088

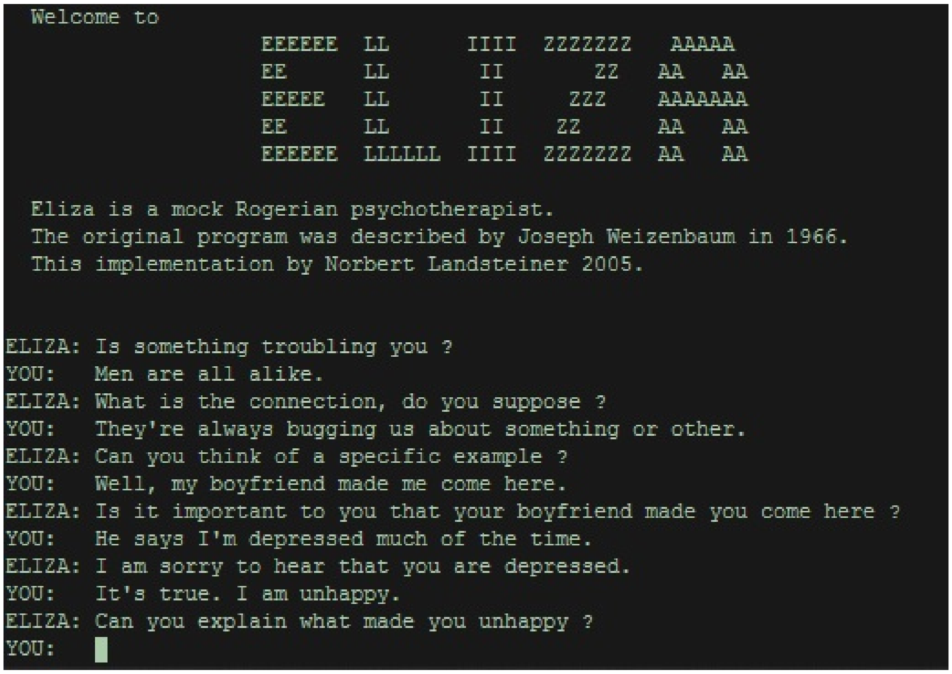

Figure 1. Photo. The first chatbot interaction.
(Source: Courtesy of unknown—public domain, https://commons.wikimedia.org/w/index.php?curid=70571280.)

It is generally accepted that no chatbot is yet "thinking" or represents "strong" AI. In some cases, chatbots can be remarkably good at understanding context, but in other instances the bot cannot respond to questions a four-year-old child would know. It is generally accepted that evolutionary intelligence or machine sentience is still years from being realized.[9]

International Business Machines (IBM) Watson represents the most successful question-answering system in history; it is famous for besting Jeopardy experts in 2011 and subsequent years.[10] This class of AI technology is generally termed ***question-answering (QA) systems*** developed using ***computational linguistics.*** Computational linguistics has been in development since the 1970s. As illustrated in figure 2, computational linguistics seeks to map the associations of nouns, verbs, and adjectives that are generally similar.[11] While Watson may seem to have many properties of generalized intelligence, it is still a "weak" AI, although quite an impressive one with a massive knowledge base.

The general knowledge responses generated by Google Home, Amazon's Alexa, and Facebook's DrQA also use computational linguistics to return the closest match to your search phrase, including searching on words and concepts that mean the same thing, but are not the specific word or phrase that you provided. IBM Watson has gone on to learn how to cook and develop its

9 http://www.kurzweilai.net/mt-notes-on-the-announcement-of-chatbot-eugene-goostman-passing-the-turing-test

10 https://en.wikipedia.org/wiki/Watson_(computer)

11 https://en.wikipedia.org/wiki/Question_answering

own recipes, as well as finish medical school.[12] If Watson could be trained to diagnose diseases and learn the protocols of medical science, it seems possible that such an AI could be trained to solve traffic control problems. For example, pouring hundreds of thousands of microsimulation models into Watson could possibly allow it to generate the rules for how cycle, splits, offsets, and sequence relate to traffic volumes and system geometry.

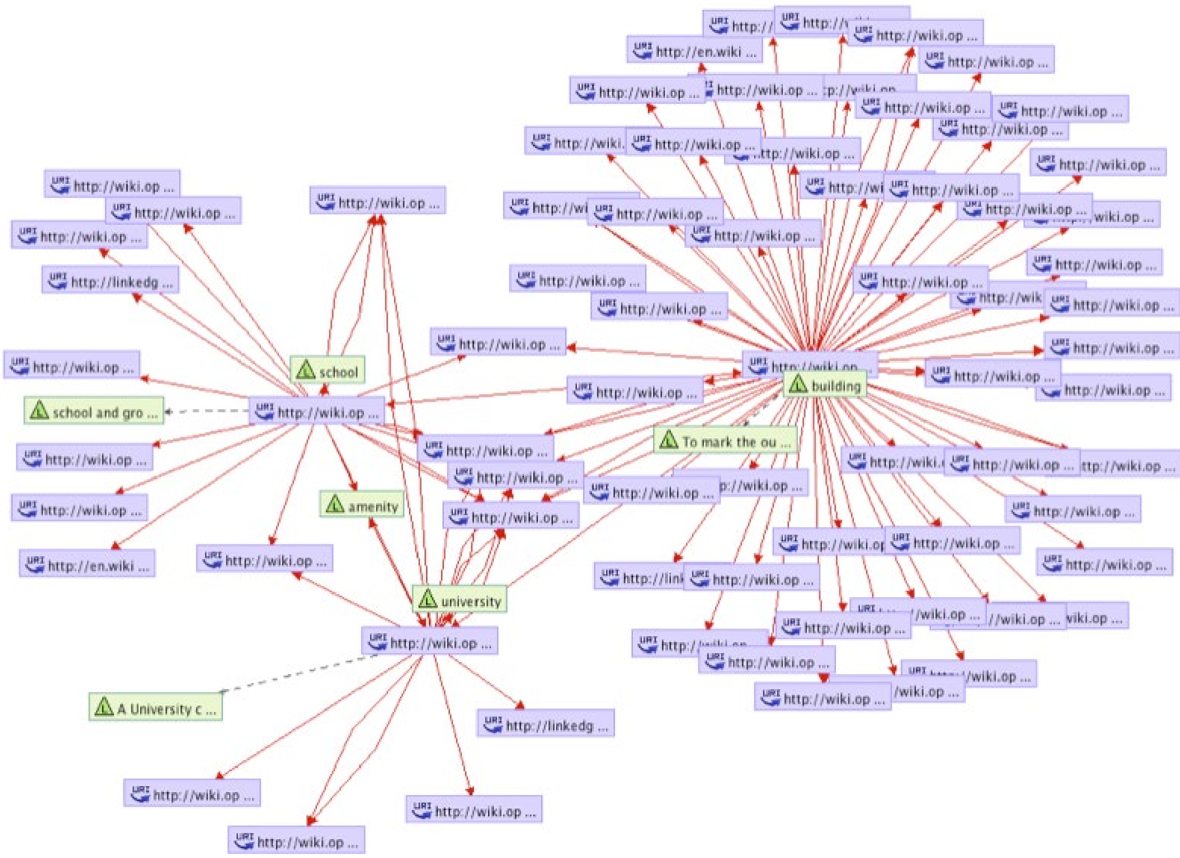

Figure 2. Diagram. A semantic network representation for just a few words and concepts. (Source: Courtesy of Andreab—https://wiki.openstreetmap.org/wiki/File:Osn_snapshot.png#filelinks, CC BY-SA 2.0 license—https://creativecommons.org/licenses/by-sa/2.0/.)

Chatbots, computational linguistics, and QA systems generally represent a category of weak AI that can be useful for various TSMO functions. It is not hard to imagine systems in the near future where general questions regarding TSMO data could be presented to a QA system in natural language (assuming the necessary data elements of the question are stored in a database), such as:

- How many crashes occurred on I-95 in Pennsylvania in August when it was raining?
- How many times was a traffic signal on Main street preempted during PM peak for more than two minutes?
- Which arterial in Montgomery County had the highest vehicle-miles traveled in June?

[12] https://www.timesofisrael.com/artificially-intelligent-watson-gets-israeli-boost-as-it-studies-medicine/

These questions would require several important "weak" AI technologies:

- Parsing the words of the user's question to decipher meaning.
- Generating the Structured Query Language (SQL) query to retrieve the result from the database or databases.
- Synthesizing the information and responding appropriately.

While no commercial off-the-shelf product can provide such generalized capability today, all the necessary components are currently in development or available in some form.

Expert Systems

The rise of ***expert systems*** in the mid-1980s generated renewed interest and enthusiasm for generalized AI capabilities.[13] Expert systems represent an expert's thought processes as a set of *if…then* rules and logic gates (e.g., AND, OR, NOT, or NAND). Specific problem areas can be tackled when provided with enough *if…then* rules. A programming language called lisp was developed to represent such logical constructs, along with many capable and useful software systems that improved a wide variety of tasks. Expert systems are still in wide use; applications include medical diagnosis, toxic waste management, nuclear reactor control, and the identification of potential remedies to system failures during space missions.

The success of expert systems in specific fields led to the theory that generalized intelligence could be constructed from symbolic logic constructs and a knowledge base (i.e., a "semantic network").[14] While the concept continues to be researched, the combinatorial explosion of the database size and the millions upon millions of rules needed to represent even basic elements of human knowledge was out of the scope of processing and database storage capabilities at the time.

Many of today's incident response modules of freeway management systems are expert systems. By encoding rules relating the dynamic message signs, closed-circuit television (CCTV) cameras, and other field elements to the location of an incident, TMC operators can quickly select a set of responses. Machine learning technologies may be able to generate the expert system rules more efficiently or creatively for decision-support systems.

Neural Networks and Supervised Learning

In the mid-1980s the concept of ***neural networks*** was revived by David Rumelhart in response to the rigidity of the expert system constructs of crisp logical rules.[15] Loosely based on the concept of biological animal brains, neural networks "learn" to do certain tasks through training (presumably like a brain is trained as children develop) and by strengthening or weakening the connections between the network of neurons based on presented input data and the expected

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[13] https://en.wikipedia.org/wiki/Expert_system

[14] http://www.cs.ox.ac.uk/people/stephen.clark/papers/aaai07brian.pdf

[15] https://en.wikipedia.org/wiki/Artificial_neural_network

output result as shown in figure 3. Neural networks are commonly applied to narrowly defined pattern recognition problems, such as image recognition (is this a cat) and data segmentation (is this a cat, a dog, a fire truck, or a tuba). Most commercial AI software platforms provide a wide variety of neural network constructs for pattern recognition problems.

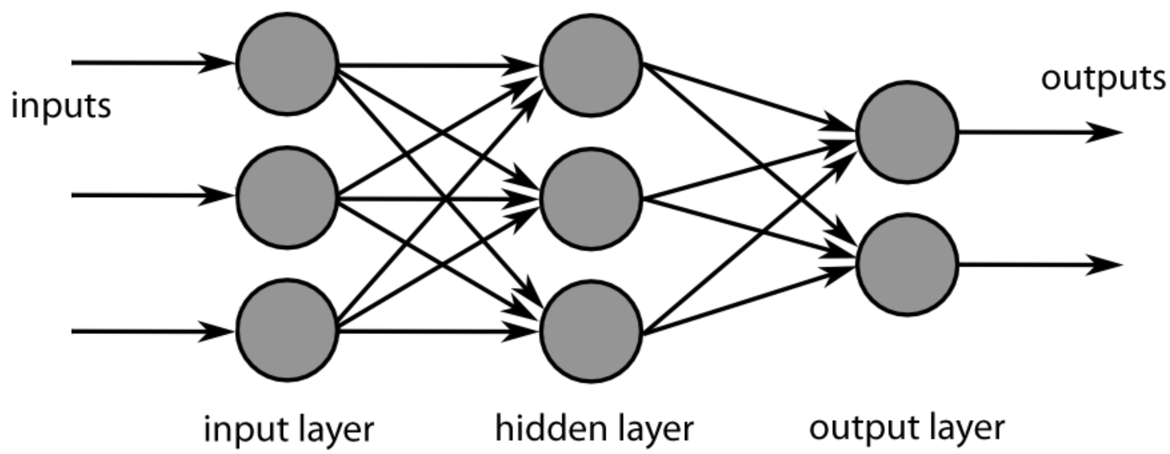

Figure 3. Flowchart. Example of a neural network.
(Source: Courtesy of Offnfopt—Own work created using File: MultiLayerNeuralNetwork english.png as a reference. Public domain, https://commons.wikimedia.org/w/index.php?curid=39500777.)

Machine learning algorithms are trained to solve specific problems using the general process shown in figure 4. An important element of the training process is feedback, which improves the model after implementation and evaluation of real-world results.

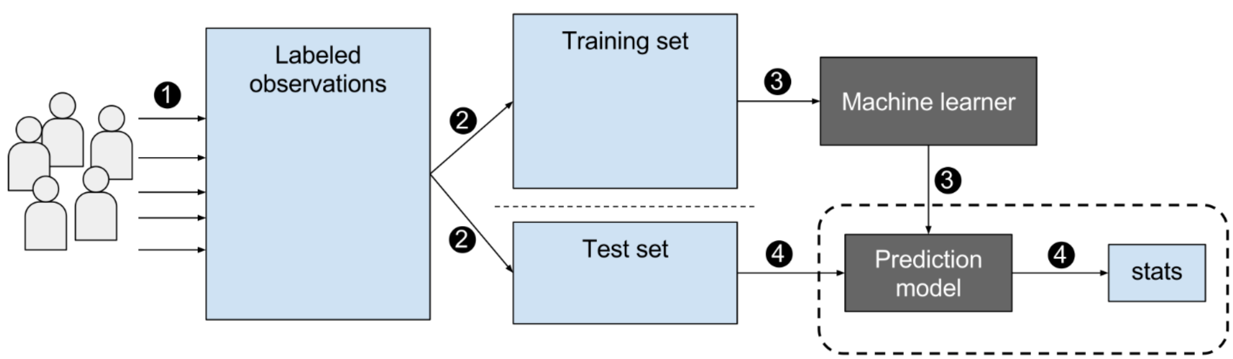

Figure 4. Flowchart. Supervised machine learning algorithm development.
(Source: By EpochFail—Own work, https://commons.wikimedia.org/w/index.php?curid=45021868, CC BY-SA 4.0 license—https://creativecommons.org/licenses/by-sa/4.0/deed.en.)[16]

The goal of representing generalized human intelligence with a brain-like structure has mostly been abandoned due to computational and database limitations. However, neural networks have found significant success in solving real problems. One example is imagery analysis, which is

16 https://www.researchgate.net/publication/315869006

well suited for the structure of a neural network, since many emergent features of images (such as object edges in the foreground and static scenes in the background) can be represented in the "layers" of the network.

The network of mathematical functions in a neural network is like a network of regression equations, such as y = a*x + b where *a* and *b* are coefficients fit to the data set. Neural networks have thousands of "a" and "b" parameters that fit to the data to represent vastly more complicated relationships between multidimensional *x* (the inputs) and *y* (the outputs). Neural networks and similar pattern recognition technologies are particularly well suited for problems that are noisy and multivariate, poorly represented by traditional models, and have highly nonlinear relationships between x and y.

Most neural network training through the early 2000s was ***supervised.*** This means that the correct output(s) for a given set of inputs are explicitly provided to the model. This is also known as providing "***labeled***" data. In imagery analysis, these labels might be that a vehicle (of any type) is in the scene or that a specific type of vehicle, such as an ambulance, is in the scene. To learn the definition of an "ambulance," many scenes with ambulances and without ambulances are provided as inputs to the model along with the correct labeling. Such pattern recognition systems are quite good at doing what you train them to do, but a common criticism is that such methods lack the ability to generalize. For example, if all images of ambulances are presented to the neural network from a side view, ambulances viewed from the front may be difficult for the neural network to correctly identify.

Many TSMO problems related to imagery analysis can be addressed by neural networks:

- Unmanned Aerial Systems (UAS) trained to identify incident details on a freeway.
- CCTV imagery analysis of crashes, debris, and pedestrians in the right-of-way.
- Counting and classifying vehicles, conducting turning movement counts, pedestrians, and cyclists.

These technologies are already on the market today and will likely continue to grow in capabilities.

Fuzzy Logic

From the late 1990s to the early 2000s, fuzzy logic was popularized after being introduced by Zadeh in the mid-1960s.[17] Fuzzy logic, like neural networks was a response to the rigidity of the expert system rule bases of the 1980s. Fuzzy logic allows "*if…then*" rules to be probabilistic in describing linguistic variables that are modified with adjectives and adverbs as shown in figure 5. A color can be "light red" and a light can be "very bright" in human speech interactions, and most people understand such meanings intuitively; people do not describe such variables as "bright" or "red" in conversation by using lumens or red, green, and blue values. Fuzzy logic has been successful in many areas of expert systems and control systems. Neural networks and fuzzy logic are sometimes combined when the input and/or output values of the neural network are

[17] https://en.wikipedia.org/wiki/Fuzzy_logic

linguistic in nature. Vice versa, neural networks are often applied to tune the fuzzy rules based on past performance.

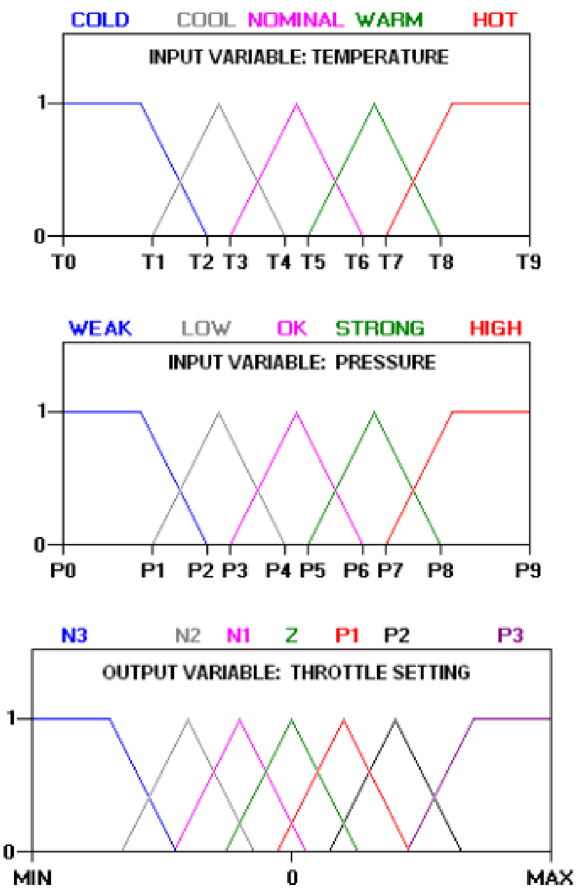

Figure 5. Graph. Example of fuzzy logic sets.
(Source: Courtesy of Boffy b at en.wikipedia.—Own work; transferred from en.wikipedia by Avicennasis using CommonsHelper. Public domain, https://commons.wikimedia.org/w/index.php?curid=10962533.)

Researchers have applied fuzzy logic to a wide variety of TSMO problems and achieved some success, particularly when applying fuzzy logic to freeway ramp metering. Ramp metering algorithms before fuzzy logic required detailed and difficult to maintain models of freeway and ramp traffic conditions. By softening the rules to general descriptions of traffic conditions ("heavy traffic," "typical traffic," "light traffic"), the algorithms become much easier for humans to write and understand. This will be highlighted in chapter 4. Many AI purists posit that fuzzy logic alone does not represent AI without the learning component of neural networks or other methodologies for revision of the rules based on past performance.

Machine Learning and Solution Search

Games are a tremendously popular application of AI and machine learning methods. In 1997, IBM Deep Blue defeated chess master Gary Kasparov in one of the most famous examples of a computer built to solve a specific problem.[18] The IBM Deep Blue supercomputer of 1997 is shown in figure 6. Chess (and *Go*, popular in Asia) is significant in the realm of ***machine learning*** paradigms because the best next move is dependent on playing out millions of potential board configurations while anticipating what an equally skilled expert opponent might do in response to each subsequent move. Deep Blue searched up to 20 rounds of potential actions in selecting the next move, mimicking generally what chess grandmasters must do in competition.[19] Additional improvements to Deep Blue's strategy were made later when the AI included the recognition of board middlegame configurations and the opponent's tactical tendencies while they were playing.

Figure 6. Photo. The Deep Blue chess-playing supercomputer in 1997.
(Source: Courtesy of Jim Gardner—
https://www.flickr.com/photos/22453761@N00/592436598/, CC BY 2.0 license—
https://creativecommons.org/licenses/by/2.0/.)

Many AI purists posit that such programs for game playing should not be called AI nor even machine learning, since they "brute force" search millions of actions according to the rules of the game and do not have "intelligence," and cannot learn from their mistakes or the actions of their opponents.

[18] https://en.wikipedia.org/wiki/Deep_Blue_(chess_computer)
[19] https://en.wikipedia.org/wiki/Deep_Blue_(chess_computer)

Many sophisticated search algorithms have been devised over the years to improve the ability of machines to find a good (and sometimes "optimal") result much faster than iterating all possible or all feasible solutions in a given amount of search time. Such search methods include ***evolutionary algorithms, genetic algorithms, ant colony optimization,*** and a host of others.[20] These methods seek to resolve the problem inherent to many search techniques in that they stop searching when they reach a local maximum or minimum. This is illustrated in figure 7.[21] Search algorithms help computer software find better solutions faster, but do not by themselves represent that the machine is learning. Much research has been done to develop search algorithms to find better solutions to common TSMO problems, such as traffic signal timings.[22]

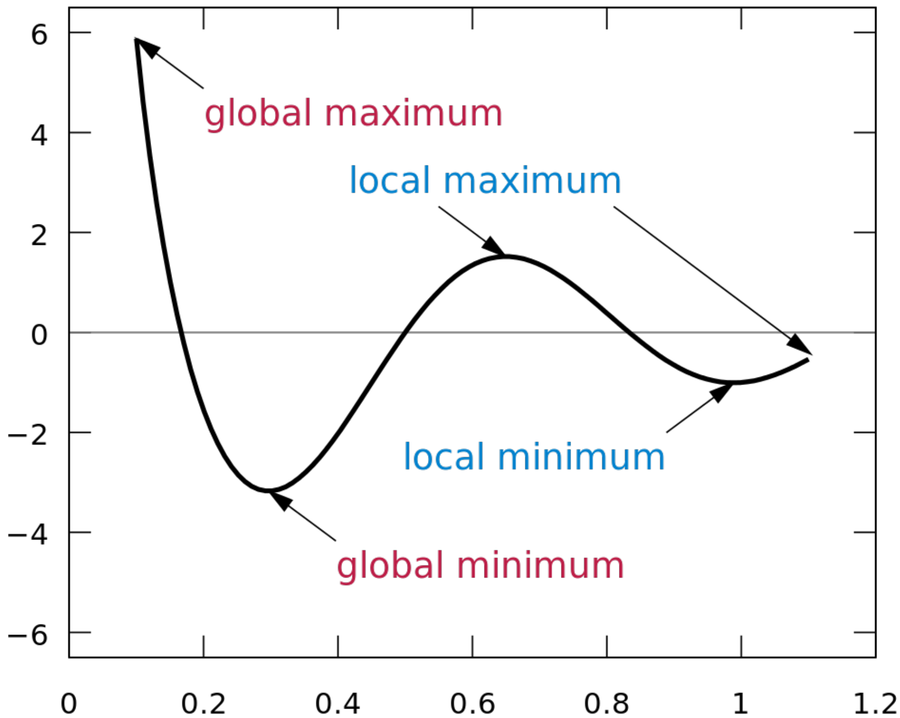

Figure 7. Graph. The problem of finding a local optimal solution instead of the global minimum or maximum using simplified search methods.
(Source: Courtesy of KSmrq kaj Maksim—https://commons.wikimedia.org/w/index.php?curid=4629984, CC BY-SA 3.0 license—https://creativecommons.org/licenses/by-sa/3.0/deed.en.)

In the last 10 years, there are now many examples of game-playing programs that do learn from their actions. Google's DeepMind software, for example, can now play and master almost any Atari 2600 game from the 1970s and 1980s, and many platforming (e.g., Super Mario) and shooting (e.g., DOOM) games that have relatively simple goals, such as reaching the end of the

20 https://en.wikipedia.org/wiki/Evolutionary_algorithm

21 https://www.geeksforgeeks.org/introduction-hill-climbing-artificial-intelligence/

22 Federal Highway Administration, *Regional Traffic Signal Operations Programs: An Overview*, October 2009, https://ops.fhwa.dot.gov/publications/fhwahop09007/index.htm

level alive with a maximum score.[23] Delaware DOT (DelDOT), for one, is piloting the use of a "game playing" AI system to find novel solutions to integrated corridor management. This pilot program is discussed in more detail in chapter 4.

Unsupervised Learning

DeepMind and other similar systems play games by learning what actions produce better scores, such as avoiding bombs in Space Invaders or bouncing the ball behind the wall of bricks in Breakout. This type of learning is generally known as ***unsupervised reinforcement learning.*** It is *unsupervised* because there is no presentation of a correct output for a given set of inputs (i.e. there is no initial set of labeled scenarios that link the correct inputs to the desired output or score). It is *reinforced,* because each action generates a certain score; the better the action, the bigger the score. Though a process of trial and error, the software system learns what inputs (e.g. movements of the paddle in Breakout) lead to the best outputs (higher scores).

Perhaps even more impressive than playing simple Atari games, OpenAI's trained neural networks known as "five" has recently defeated and continues to best teams of professional Dota 2[24] e-sports players in a best of three match.[25] The game Dota 2 requires extensive cooperation between a team of five characters with a variety of abilities. OpenAI's "five" plays 180 years of matches against itself every day to learn strategy, tactics, and cooperation.[26] The achievement is considered substantial in the world of AI by Bill Gates and other industry experts as evidenced in figure 8.[27] The formulation of the congestion minimization problem as a "game" (i.e., TMC operator versus the network) might find some promise in coming years, since the outcomes of certain TMC operator actions cannot be known for certain.

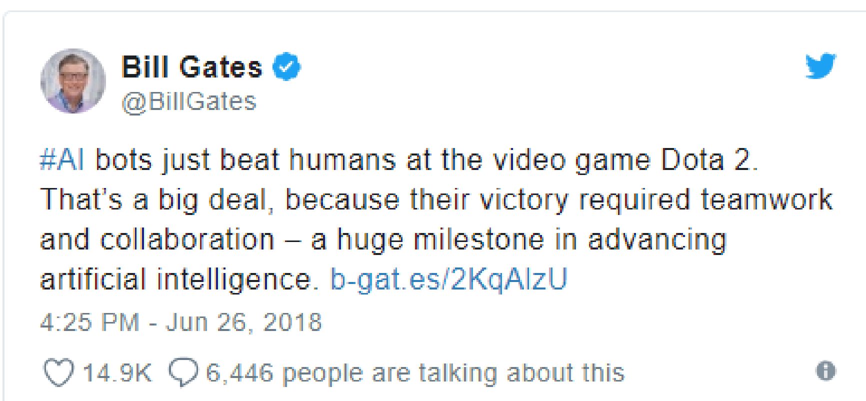

Figure 8. Screenshot. Bill Gates' tweet regarding OpenAI's defeat of expert human players.
(Source: Twitter: fair-use policy.)

[23] https://becominghuman.ai/lets-build-an-atari-ai-part-1-dqn-df57e8ff3b26
[24] Dota 2 is one of the most popular multiplayer online battle games in personal computer history and includes leagues of professional paid players.
[25] https://blog.openai.com/openai-five-benchmark-results/
[26] https://blog.openai.com/openai-five/#restricted
[27] https://openai.com/five/

DeepMind and OpenAI "five" are examples of the general class of machine learning methods now known as ***deep learning.*** In the case of DeepMind, the game representation is a special type of neural network, which is a commonly applied to imagery analysis since each neuron is loosely modeled after the visual cortex of a human (or animal) eye. In general, deep learning methods have multiple internal ***layers*** of feature representation. OpenAI "five" has those properties in that it "sees" the Dota 2 battlefield just like a human player would and classifies the static and dynamic objects on each image in evaluating what action(s) to take. Marketing materials for AI tools and technologies frequently use "deep learning" to loosely refer to almost any machine learning technology, but formally deep learning refers to a system that learns patterns without supervision.

Robotics and Driverless Vehicles

Robotics is the physical embodiment of machines that can substitute for humans and replicate human actions.[28] Robots are typically best suited for tasks that are "dull, dirty, and dangerous." Hundreds of robotic applications are commonplace in warehouses, vehicle manufacturing, explosives disposal, surgery, and agriculture, with thousands more envisioned for the future.[29, 30] The use of UASs (though manually operated, typically) for bridge inspection, site survey, and other transportation-related activities is rapidly expanding. A prototype delivery UAS is depicted in figure 9. It is easy to envision autonomous or semi-autonomous UASs improving TSMO activities in the future. In April 2019, Google's Wing UAS received the first Federal Aviation Administration approval for package delivery.[31]

[28] https://en.wikipedia.org/wiki/Robotics
[29] https://venturebeat.com/2018/09/11/alphabets-loon-internet-balloons-can-now-fly-600-kilometers-apart/?utm_source=VentureBeat&utm_campaign=7f07ab0d07-AIWeekly&utm_medium=email&utm_term=0_89d8059242-7f07ab0d07-9168645
[30] https://venturebeat.com/2018/07/11/alphabets-x-graduates-its-loon-and-wing-moonshots-into-standalone-companies/
[31] http://onlinepubs.trb.org/onlinepubs/circulars/ec168.pdf

Figure 9. Photo. Delivery drone prototype.
(Source: Courtesy of Mollyrose89, own work—
https://commons.wikimedia.org/w/index.php?curid=70782694, CC BY-SA 4.0 license—
https://creativecommons.org/licenses/by-sa/4.0/deed.en.)

Driverless vehicles are a good example of the combination of AI techniques, robotics, computers, and sensors. The concept of driverless systems has been around since the 1930s but have only recently become viable with the current capabilities and affordability of sensors, miniaturized computers, mapping, and software systems.[32] AI is used in driverless vehicles in several manners:

- Neural networks are used to detect and classify objects from light detection and ranging (LiDAR) and video inputs.
- Neural networks and similar machine learning technologies are used to fuse sensor data from multiple inputs for improving object classification (e.g., if the video and the LiDAR sensors both conclude the object is a "pedestrian," it is probably a pedestrian. If one sensor/algorithm concludes "pedestrian" and the other "bicycle," check again).
- Some AI driver models are trained to drive from watching the behavior of (good) human drivers.
- Some AI driver models are trained by unsupervised reinforcement learning in simulated three-dimensional (3D) environments.
- Anomalies in embedded maps are identified using machine learning.

Generally, driverless vehicles combine real-time LiDAR, video, and radar sensors with embedded neural network AI, high-powered computers, high-resolution digital (3D) maps, and driving algorithms (some of which also use AI models to determine what actions to take next).

32 https://www.marketwatch.com/story/teslas-latest-autopilot-update-is-still-not-hands-free-2015-10-14

Driverless vehicles are still far from perfect, as evidenced by crashes with fire trucks,[33, 34] and the recent fatalities of drivers and pedestrians.[35, 36] Driverless vehicles will become a reality; the question is no longer "if," but "when." A driverless vehicle without a steering wheel or pedals is shown in figure 10.

The various uses and impacts of driverless vehicles on TSMO operations is commonly discussed. Speculation ranges from a utopian view of a congestion-less future and a happily ridesharing public that owns no personal conveyance, to the dystopian predictions of status quo or even more congested roadways as zero-occupancy vehicles roam the roads looking for their next fare rather than parking for 95 percent of the day as most vehicles are today.

Figure 10. Photo. Interior of a driverless car prototype.
(Source: Courtesy of David Castor, own work—
https://commons.wikimedia.org/w/index.php?curid=57907940, public domain.)

[33] https://www.wired.com/story/tesla-autopilot-why-crash-radar/
[34] https://www.cbsnews.com/news/tesla-autopilot-crash-utah-fire-truck-driver-elon-musk-bemoans-attention/
[35] https://www.wired.com/story/tesla-autopilot-self-driving-crash-california/
[36] http://www.thedrive.com/tech/19427/uber-pedestrian-accident-death-might-force-self-driving-car-makers-to-hit-the-brakes-on-autonomy

Use of driverless vehicles and airborne UASs will likely find a variety of uses for TSMO, including:

- Crash-abatement vehicles at incident and work zone sites can be made driverless and controlled by operators with hand signals or made to follow human-driven trucks automatically.[37]
- Incident management surveillance with airborne UASs, particularly in rural areas. Airborne imagery analysis and classification is illustrated in figure 11.[38, 39]
- Equipment and materials delivery.
- General passenger-carrying automated vehicles relieving TSMO staff of the burden of driving enabling more productivity en route to job sites.
- Automated classification of ground objects from 3D LiDAR point clouds using neural networks.[40]

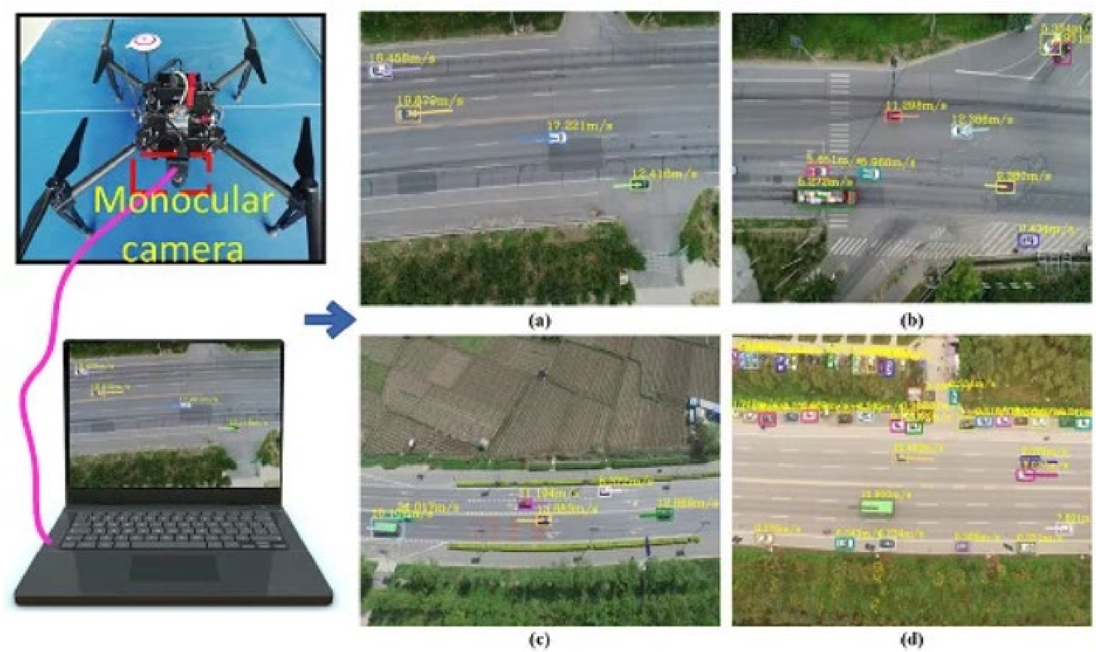

Figure 11. Photo. Automated identification of traffic features from airborne unmanned aerial systems.
(Source: https://www.mdpi.com/2072-4292/11/10/1241?tdsourcetag=s_pctim_aiomsg, CC BY 4.0 license—https://creativecommons.org/licenses/by/4.0/.)

37 https://www.wired.com/story/this-lumbering-self-driving-truck-is-designed-to-get-hit/
38 https://policy.tti.tamu.edu/congestion/operations-and-policy-implications-for-unmanned-aircraft-systems-for-traffic-incident-management/
39 https://medium.com/nanonets/how-we-flew-a-drone-to-monitor-construction-projects-in-africa-using-deep-learning-b792f5c9c471
40 https://www.pix4d.com/blog/machine-learning-meets-photogrammetry/

Summary

AI and machine learning technologies will likely enable IOOs to increase the sophisticated use of *analytics* and *data* to support TSMO activities. Chatbots and QA systems may enable new ways to obtain insights in data. Neural networks will analyze imagery from a variety of sources for incident detection, incident management, and traffic data collection. Fuzzy logic is already used by a variety of DOTs for ramp metering and they may find additional applications by simplifying *if…then* rule bases for decision-support systems. Unsupervised AI systems may learn new ways to control traffic and coordinate integrated corridor management actions across a variety of control and advisory technologies. Driverless vehicles and airborne and ground-based drones will likely improve TSMO staff safety and productivity. Additional applications are likely to arise as agencies gain experience with AI tools and technologies.

No generalized human-like intelligence (or "strong" AI) is available today or envisioned to be available anytime soon. Machine learning technologies are trained by supervised or unsupervised methods. Neural networks are the most popular form of machine learning methods, particularly for imagery analysis. Significant investments in driverless vehicles and UASs will likely see near-term applications that will affect a wide variety of TSMO functions.

The next chapter discusses some commercial AI computing platforms. As commercial companies continue to quickly add to their system capabilities, feature sets will continue to evolve, systems will continue to become easier to use, and the cost of ownership or use will decrease. This view of commercial capabilities should be considered just a snapshot of early 2019. The use of product names and specific tools does not constitute an endorsement of these technologies.

CHAPTER 3. COMMERCIALIZATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES

In this chapter, the capabilities of commercial artificial intelligence (AI) platforms will be presented. In software terminology, a "platform" generally describes a suite of software applications and components that work together to address a variety of functions. Since there are hundreds if not thousands of commercial offerings, this chapter will focus on the major offerings from Google, Microsoft, and Amazon and specialty categories relevant to transportation systems management and operations (TSMO). As all commercial companies continue to quickly add to their capabilities, feature sets will likely continue to evolve, platforms will continue to become easier to use, and cost of ownership or use is likely to decrease. This view of commercial capabilities should be considered just a snapshot of early 2019 and should not be considered an endorsement of any particular provider or technology services. After reading this chapter, you should have an appreciation of the technical maturity and capabilities of major platforms for development of AI applications.

This chapter is organized as follows:

- The state of the practice in commercialization of AI.
- A summary of the capabilities of major AI technologies offered by Google, Amazon, and Microsoft.
- Expected AI capabilities in the future based on current publicized roadmaps from major platform providers.
- How such systems and technologies are typically procured and monetized.

STATE OF THE PRACTICE AND COMMERCIALIZATION OF ARTIFICIAL INTELLIGENCE

There are almost 1,000 commercial companies involved in providing software and services in some way or another related to AI. According to Gartner, widespread adoption of AI is still emerging across all industries.[41] It would generally be true that the larger the organization, the more likely they would be to adopt or pilot AI technologies. Costs associated with software procurement, software development, and database development and population can be substantial while the corresponding expected improvements may be unknown. Larger organizations (from a TSMO perspective, this would imply larger State departments of transportation (DOT) and the largest cities) generally have more tolerance for downside investment risk with the potential for substantial at-scale benefits if successful.

AI technologies also integrate common functions of business intelligence (BI) technologies include reporting, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and prescriptive analytics. Typically, AI technologies are used to handle large amounts

[41] https://www.gartner.com/en/doc/3872663-deliver-artificial-intelligence-business-value-a-gartner-trend-insight-report

of structured and sometimes unstructured data and aim to allow for the easy interpretation or use of this data. In commercial terms, AI is envisioned to provide users of the various technologies with a competitive advantage by identifying new opportunities and implementing an effective strategy based on insights.[42] For infrastructure owners and operators (IOO), use of AI in its various forms may reduce costs, augment staff, improve staff efficiency, provide suggested solutions that humans may not have thought through in advance, and provide conveniences in the transportation management center (TMC) similar to those enjoyed by staff on their personal time such as turning on lights and voice activation of other actions. IOOs will need to consider if it is more effective to purchase such AI functions as a service (aaS) or develop and maintain such applications on-premise or in-house. With the current state of the practice in AI, the answer will likely be some hybrid of both methods where AI solution providers/vendors (which could include universities in addition to private companies) use "aaS" technologies in software that is sold to the IOO as a packaged software product.

Some examples of commercially-available AI applications include:

- Natural language processing and natural speech synthesis of digital assistants. Progress in speech synthesis and capture has been significant in just the last five years. 511 systems may be enhanced with such technology.

- Integrated chatbots in virtual assistants enables new ways to interact with software systems. Conversational skills of virtual assistants are likely to continue to increase in the coming years as the software is trained to understand the context of your actions and carry out tasks on your behalf.[43,44] TMC operations may be automated and streamlined.

- All major cloud service providers (Google Cloud, Amazon Web Services, Microsoft Azure) now support suites of AI-related tools and software services. AI suites may prove useful to IOOs in developing AI applications with less development time and cost.

- Object recognition and tracking software is commercialized widely, including companies focused solely on the traffic and transportation market. Incident detection and management may be significantly affected.

- Driverless vehicles and unmanned aerial systems (UAS) are likely to be available in the near term for use by IOOs in a variety of applications, including crash abatement, asset surveillance, and equipment delivery.

42 https://en.wikipedia.org/wiki/Business_intelligence

43 https://venturebeat.com/2018/09/20/12-ways-alexa-is-getting-smarter/?utm_source=VentureBeat&utm_campaign=10004e258a-AIWeekly&utm_medium=email&utm_term=0_89d8059242-10004e258a-9168645

44 https://www.theverge.com/2018/12/5/18123785/google-duplex-how-to-use-reservations

Commercial Artificial Intelligence Platforms

As stated previously, in software technology, a "platform" generally describes a suite of technologies that are used together to build applications. This typically describes the combination of databases, algorithms, user interfaces, application programming interfaces (API), computing resources and operating systems, testing software, development languages, and other supporting software and hardware. For curious readers with limited software development experience, browsing any of the commercial provider's websites to learn more about any of the tools and components may be challenging. While most platform providers supply an array of tutorials and "quick start guides," most require extensive experience with databases, programming (particularly python), and knowledge of technical jargon related to machine learning and advanced statistics.

Given the many tools that could all combine and overlap to produce one comprehensive AI solution, several deployment options are available based on computing capabilities of the IOO and their information technology (IT) policies on data security and privacy. Figure 12 shows the range of implementation options available.

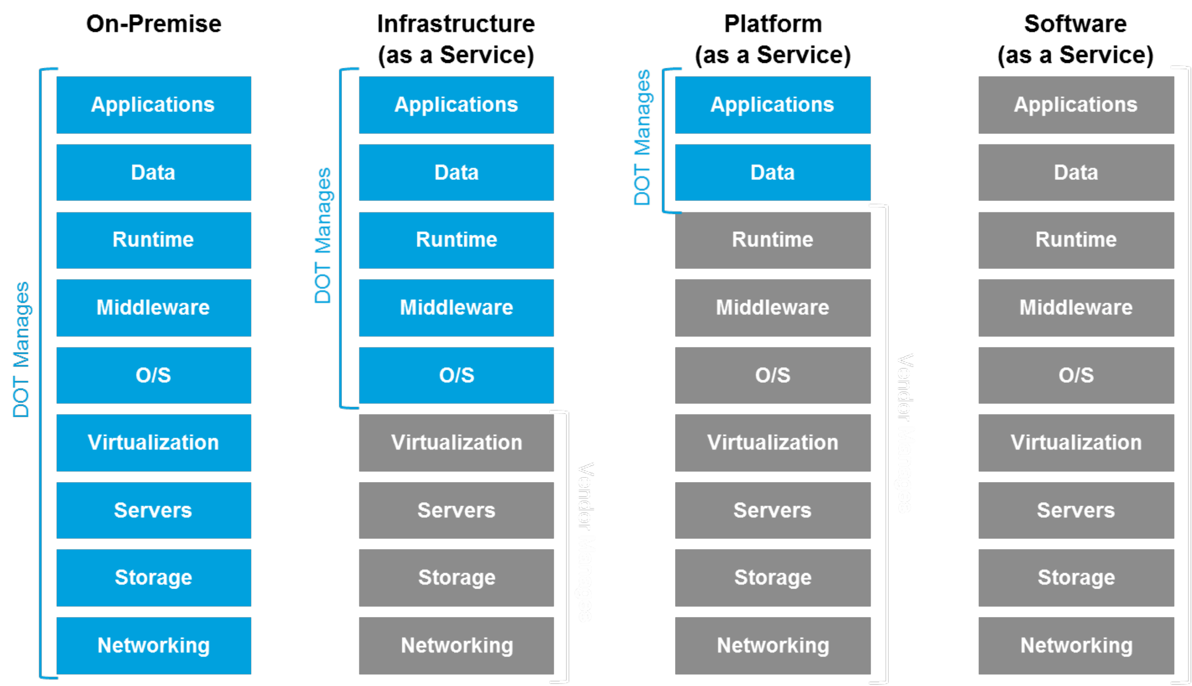

Figure 12. Chart. Information technology considerations for on-premise, infrastructure-as-a-service, platform-as-a-service, and software-as-a-service implementations.
(Source: Deloitte, 2016.)

The "as a service" (aaS) models generally assume a cloud-based deployment (gray boxes) for the aspects of control an organization is willing to sacrifice for simplicity and possibly cost savings.

- **On-Premise:** Deployment offers users the ability to install, manage, and maintain every aspect of a system deployment. Typical on-premise deployments require significant up-front costs (hardware, software licensing, etc.), but allow for greater control of the system.

- **Infrastructure-as-a-Service (IaaS):** Deployment provides scalability needs and minimizes responsibility for the DOT. Users are responsible for managing applications, data, runtime, middleware, and operating system. Instead of having to purchase hardware outright, users can purchase IaaS based on consumption (such as database reads/writes, or computing cycles), similar to electricity or other utility billing.

- **Platform-as-a-Service (PaaS):** Deployment allows users to develop, test, and deploy applications quickly and efficiently. With PaaS, users are only responsible for data and application tiers. Similar to IaaS, users can purchase PaaS on a subscription basis ultimately paying just for what they use.

- **Software-as-a-Service (SaaS):** Deployment uses the Web to deliver applications. Most SaaS applications can be easily accessed directly from a Web browser on the client's side. This model is maintained entirely by the vendor. Like the other service models, users typically purchase a subscription to access the application.

Note that for the major commercial providers detailed in this chapter, none are available as "on-premise." Cloud services for technologies that rapidly evolve (which includes AI) allow developers and providers to more seamlessly provide new functionality and enhancements to the end customer/user without (sometimes) complex installation processes.

Google Cloud Artificial Intelligence

The Google Cloud AI platform includes the necessary elements to build and train machine learning neural network models for a variety of applications. ***TensorFlow*** is a popular neural network tool used across a variety of industries for imagery analysis, natural language processing (NLP), and other unique applications such as automated piano audio transcription. Other elements of the Google Cloud ecosystem include ***DialogFlow, Actions,*** and ***Firebase,*** which are used for Chatbot development and integration of question-answering applications with Google Assistant.

Since TensorFlow is an open-source software, it is also available on other platforms, including Amazon and Microsoft, among hundreds of other AI platforms. Google has stated that they will continue to develop new modules in their AI ecosystem that make machine learning development less and less about programming and computer science and more about data science and analysis. In addition, tools like ***Cloud AutoML*** are being provided more rapid identification of the "right" neural network model architecture for the specific application.[45] Many neural network applications considered by IOOs (traffic imagery analysis, in particular)

[45] This is a significant development, as the process of developing the "right" model for a specific pattern recognition problem has required a lot of trial and error for the past 20 years.

will likely include some use of TensorFlow or similar technologies to differentiate between normal and abnormal conditions in a messy data set, such as incident and nonincident conditions.

Google's ***Duplex*** technology,[46] while not commercially available to write apps against yet, represents their next generation of chatbot technology that can make phone calls to humans and perform basic tasks. In their demonstrations, the chatbot makes reservations for dinner and schedules hair appointments (neither which may seem remotely related to TSMO), but the potential for the technology to communicate to humans and respond to them in context is a stepping stone to more relevant activities such as communicating instructions to technicians, coordinating among agencies, performing incident management activities, and modifying traffic signal timings.

One other Google AI technology that is emerging is ***Temporal Action Localization.***[47] This technology allows object recognition in video streams by associating certain moments in the video with context. While again, Google demonstrates the technology with consumer applications of videos of children playing ("sliding on a slide") and babies being fed with a spoon, the extension to TSMO business applications may be able to take incident detection and video image analysis beyond the realm of existing approaches. TMC operators (or applications in real time) could search thousands of camera feeds simultaneously for "slow traffic where typically not" and many other different kinds of potential natural language queries.

Microsoft Azure Artificial Intelligence

Microsoft provides a suite of tools and technologies for machine learning and AI application development, including neural network models, AI apps and chatbots, and ***"Cognitive Services,"*** which are prebuilt neural networks that are available to solve common problems (specific object recognition in images, most commonly) using your specific data sets. Cognitive Services also provide functionality, such as removing offensive content from images and videos, extracting key phrases from volumes of text, and automated text translation into multiple languages.

Microsoft (and both Google and Amazon) also release early-access "alpha" tools and services as **Labs.**[48] These AI tools allow experimentation with new features and services.

Two of these labs are particularly relevant to TSMO applications, namely ***"project knowledge exploration"***[49] and ***"project anomaly finder."***[50] Project knowledge exploration is Microsoft's effort to turn natural language questions into Structured Query Language (SQL) queries. As this technology continues to progress, questions such as, "how many ramp meters had more than 1000 vehicles per hour flow in the PM peak period" or "which traffic signal had the most emergency vehicle preemptions in November 2018," will be enabled without prewritten SQL queries or customized reporting and such questions can be asked by voice. Project Anomaly

46 https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html
47 https://ai.googleblog.com/2019/04/capturing-special-video-moments-with.html
48 https://www.microsoft.com/en-us/ai/ai-lab
49 https://labs.cognitive.microsoft.com/en-us/project-knowledge-exploration
50 https://www.microsoft.com/en-us/research/project/anomaly-finder/

Finder offers the potential for transportation management system (TMS) modules to analyze and report problems with field equipment without extensive software development. Currently, TMS applications typically have extensive code specifically designed for anomaly detection of various device types. Costly software development is typically required when new types of anomaly analysis is needed.

Amazon Artificial Intelligence on Amazon Web Services

Similar to Google and Microsoft, Amazon offers a suite of AI tools and technologies as part of its Amazon Web Services ecosystem, centered around ***Lex, Polly, Rekognition,*** and ***SageMaker.***[51] Lex and Polly represent the suite of tools that power Amazon Alexa. Rekognition is for imagery analysis (as with Microsoft and Google, using deep learning neural networks). SageMaker is Amazon's suite of tools for machine learning and training various types of neural networks.

Like Google and Microsoft, Amazon offers "preview" services that will be launched soon, including ***Forecast*** that claims can be used with no machine learning expertise, although a deep understanding of regression models and forecasting background is recommended.[52]

Procuring and Using Artificial Intelligence Platforms for TSMO

Most TSMO agencies procure TMS applications from vendors and those vendors will likely use components from open-source tools provided by major platforms other third-party AI software providers to integrate AI into existing applications and in developing new applications. Procurement and pricing of platforms, software, and computing resources aaS is a complex undertaking. Procuring software on a subscription basis is an emerging practice for most DOTs and it is quite difficult to estimate how much an application will cost. Pricing models vary based on computing cycles, data storage size, frequency of analytics, and other metrics. Since AI applications will be new, costs will likely be extensive in the beginning and become more affordable over time. A lot of care will need to be taken to architect an AI system, so it does not become price prohibitive to store and process data in the Cloud, or via massive on-premise computing resources and databases. IOOs should consider if it is more effective to purchase such AI functions *aaS* or develop and maintain such applications on-premise or in-house. Considering the current state of the practice in AI, the answer will likely be some hybrid of both methods where AI solution providers/vendors (which could include universities in addition to private companies) use aaS technologies in software that is sold to the IOO as a packaged software product.

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51 https://aws.amazon.com/machine-learning/

52 https://aws.amazon.com/forecast/

Specialty Categories of Commercial Artificial Intelligence Offerings for TSMO

Computer Vision Processing

There are several companies that now provide AI-based computer vision processing for traffic, including MioVision, Gridsmart, NoTraffic, GoodVision, Waycare, and a host of others. These products are not endorsed by this report but used only as examples of existing commercial offerings to illustrate the rapidly increasing availability of AI (typically using neural networks for object recognition) in video analysis hardware. Newer camera systems can now track vehicles and objects in their field of view without superimposing detection zones on the image.[53, 54, 55, 56, 57, 58] Anomalous activities, such as persons walking across a freeway or crashes are flagged. Performance of such systems typically depend on the variances in the background (shadows, weather) and other aspects of the video quality. Patented (and open-source) methods using machine learning techniques are now available that post-process video content for applications such as traffic counting and vehicle classification studies.[59, 60]

Some of these systems work with their own cameras and others are central software that process digital video from other cameras. Centralized processing of closed-circuit television (CCTV) video will likely become more prevalent as the technology continues to mature to handle variances in image sources, such as camera positioning, resolution, and clutter in the traffic scene. The promise of capturing multimodal users, counting turning movements, and acquiring trajectory data of vehicles from video streams will significantly enhance a variety of TSMO applications.

Driverless Systems (Ground)

Driverless vehicles are emerging, but even so the *ubiquitous* availability of such technology is still far in the future. A driverless shuttle is illustrated in figure 13. Driverless vehicles are being developed primarily now by the private sector and as such they are proprietary offerings, although there is still much university research ongoing to develop new approaches. A handful of aftermarket startups are planning to offer retrofit kits, while it remains to be seen how such retrofits would work with existing agency-owned assets such as maintenance trucks. Essentially, all vehicle original equipment manufacturers are developing integrated automation packages or are partnering with other developers to supply the software systems for automated driving.

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[53] https://www.telegra-europe.com/solutions/solution-54
[54] http://www.intuvisiontech.com/intuvisionVA_solutions/intuvisionVA_traffic.php
[55] https://link.springer.com/book/10.1007/978-3-319-52081-0
[56] https://global-sei.com/its/products/aid.html
[57] https://en.wikipedia.org/wiki/Artificial_intelligence_for_video_surveillance
[58] https://www.mdpi.com/1424-8220/12/8/10407/htm
[59] http://www.trafficvision.com/
[60] https://www.youtube.com/watch?v=FM22gwXvFCw

Figure 13. Photo. Driverless shuttle.
(Source: Courtesy of Pjotr Mahhonin, own work—https://commons.wikimedia.org/w/index.php?curid=61366346, CC BY-SA 4.0 license—https://creativecommons.org/licenses/by-sa/4.0/deed.en.)

Driverless Systems (Air)

Similar to automated ground vehicles, UASs are also typically proprietary and closed systems with integrated command and control software that only manages UASs made by the same manufacturer. Line-of-sight UAS operation is now common and applied in a variety of industries. Beyond visual line of sight (BVLOS) and related airspace deconfliction and safety regulations are necessary policies for deployment of autonomous UASs for public agency use, including public safety agencies. The near-term benefits of autonomous UASs for TSMO could be substantial, but depending on the development of acceptable use regulations, technical standards, and operating policies. These regulatory and policy developments will be required along with the resolution of technical challenges of autonomous flight, sense-and-avoid, intervehicle communication, and mission tasking. The use of a UAS for construction surveillance is illustrated in figure 14.

Figure 14. Photo. Unmanned aerial systems for construction inspection.
(Source: Courtesy of Oregon Department of Transportation—Inspecting with drones, https://flickr.com/photos/28364885@N02/33334339961, CC BY 2.0 license—https://creativecommons.org/licenses/by/2.0/.)

Future Directions and Likely Timeframes for Maturity of Artificial Intelligence Technologies

Due to the potential of AI applications across a variety of industries, Microsoft, Google, Amazon, International Business Machines (IBM), and thousands of start-ups and other major corporations and Government agencies are pouring substantial investment into AI. One trend is the migration of some AI software to purpose-built AI hardware. This is not surprising as it has been the trend of essentially all previous software tech (that is required to run in real time) to be transitioned from software to hardware to be effective. For example, Optical Character Recognition (OCR) was once only available to the Postal Service, but now anyone can buy a $40 multifunction printer/copier, which can provide OCR translation of any scanned document. The OCR process in such a device is embedded in a microprocessor chip that is quite inexpensive.

Microsoft's project ***Brainwave*** is one such effort to move ***Azure Machine Learning*** technologies to hardware to provide real-time performance of anomaly detection in high-speed processes, such as production lines or magnetic resonance imaging machines, for example.[61] In the near term, IOOs will probably not require purpose-built AI hardware for any specific

[61] https://www.aitrends.com/business/microsofts-ai-roadmap-updated/

application or the AI hardware will be embedded in the procurement of the application or system (e.g., driverless vehicles with specialized AI processors on board).

Other major AI efforts at Microsoft focus on healthcare and genomics, customer relationship management, and digital assistants, as well as integration of their Azure Machine Learning technologies with their popular ***Power BI*** business intelligence desktop tool.[62] Many IOOs that have standardized on the Microsoft Office family of software products may have some use of Power BI already or are considering Power BI for various data analysis and "dashboard" applications.

Google AI is focused on improving image recognition performance with ***AutoML*** by leveraging their global database of images to transfer learning of their own models to yours, reducing the number of training images from hundreds of thousands to a few hundred.[63] Similarly, their focus in 2019 and beyond is reducing the expertise necessary to stand up an AI system, since the gap between AI talent (software and database specialists with understanding of AI technologies) and the need for AI developers is significant. Google expects products such as ***AI Hub, KubeFlow Pipeline, Deep Learning Virtual Machines, AI Platform*** (beta), and ***Dopamine***,[64] to help continue to close the gap between the need for software engineering expertise and viable AI applications. Both of these focus areas are critical for IOO uses of AI technology. First, imagery analysis is probably the number one application of AI to TSMO functions and second, IOOs (in general) typically lack the software and database expertise to develop and maintain AI applications internally.

The digital assistant direction for Google is centered around ***Duplex*** (as discussed earlier). While currently Duplex is focused on making phone calls for tasks such as scheduling appointments, the technology that enables context-sensitive conversations will open up new avenues for digital assistants. As consumers can currently turn on and off lights, set the thermostat, and perform other household actions through voice commands, many TMC operations will likely be able to become voice enabled for those agencies that are so inclined.

Amazon's strategy is comprehensive and focused on AI-purposed hardware and chips (project ***Nitro***),[65] making data lakes easier to stand up,[66] and providing training modules on how to use their suite of software products. Amazon also launched a machine learning model marketplace, ***SageMaker GroundTruth,*** which automates data labeling in training sets, and ***RoboMaker***, a service that helps developers build and deploy robotic applications (and a $400 miniature autonomous vehicle called ***DeepRacer*** for developing automated driving and a racing league to go with it).[67] Similar to the implications of Google and Microsoft's future strategies on IOOs, the

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62 https://docs.microsoft.com/en-us/power-bi/service-machine-learning-automated
63 https://www.solstice.com/fwd/ai-google
64 https://opensource.google.com/projects/dopamine
65 https://aws.amazon.com/about-aws/whats-new/2018/07/amazon-ec2-nitro-system-based-instances-now-support-faster-ebs-optimized-performance/
66 https://aws.amazon.com/big-data/datalakes-and-analytics/
67 https://venturebeat.com/2018/11/30/ai-weekly-6-important-machine-learning-developments-from-aws-reinvent/

general trend of Amazon's services is towards simplification of development of AI applications for use by more and more customers without deep knowledge of software development and database management.

SUMMARY OF COMMERCIAL ARTIFICIAL INTELLIGENCE DEVELOPMENT

There are thousands of companies competing for dollars in the AI space across essentially every consumer and Government market as the technology continues to mature. Technologies from major platform providers and open-source tools they have either developed or adopted tend to underpin most software and hardware AI products. As with Big Data a few years ago, hype in the capabilities of AI is at a peak. As time moves on, these technologies will come closer and closer to "plug and play," but currently there is still a reasonably large barrier between the dreams of AI-enabled TSMO applications and the need for significant expertise and investment to make those dreams a reality. As fast as the pace of development of AI tools and technologies is progressing, within the next five years, AI applications may find their way from research experiments and pilot demonstrations to fully scalable applications.

Common trends in AI development over the next five years, according to Forbes, will be:[68]

- Development of AI-specific hardware chips for embedding machine learning and training in consumer products, industrial processes, and vehicles.
- Movement of machine learning models from centralized Cloud systems to edge Internet of Things (IoT) devices.
- Interoperability among neural network modeling systems and frameworks via Open Neural Network Exchange (ONNX), a platform-neutral standard supported by the AI industry.[69]
- Automated machine learning with AutoML—speeding the process of building and deploying neural networks.
- Application of AI analysis to IT operations.
- Continued evolution of chatbots and virtual assistants into more comprehensive, context-sensitive question and answering functions.
- Deployment of consumer-ready automated vehicle services.
- Democratization of machine learning services and software to professionals without deep software development and database management skills.
- Improvement of AI responsibility, transparency, and morality; the removal of systematic biases against minorities.

In the field of digital video processing, since existing products have already emerged for TSMO, the pace may be faster. Driverless vehicles are likely to be available to TSMO agencies within the near term and BVLOS-automated UAS operations in the medium term. In the next chapter we present some case studies of AI-enabled applications at DOTs that have been deployed already or are in the process of being piloted.

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[68] https://www.forbes.com/sites/janakirammsv/2018/12/09/5-artificial-intelligence-trends-to-watch-out-for-in-2019/#36206b356183

[69] https://onnx.ai/

CHAPTER 4. ARTIFICIAL INTELLIGENCE FOR TSMO APPLICATIONS

In this chapter, you will learn that use of artificial intelligence (AI) technologies in transportation systems management and operations (TSMO) is not completely new. A handful of AI applications have been deployed at transportation management centers (TMC) in the U.S. already or are in the process of being implemented. These projects are highlighted, and lessons learned are noted, where available. From these experiences, some issues to be considered in applying AI to TSMO applications are identified and detailed in chapter 5.

This chapter provides AI examples in incident detection, ramp metering, traffic prediction, and chatbot decision support. In each section, highlights of each application include the potential or actual benefits of an AI approach over traditional methods and the agency's plan for expansion and use.

ARTIFICIAL INTELLIGENCE FOR INCIDENT DETECTION

Traditional software methods for incident detection using vehicle detectors, either via in-pavement inductive loops or shoulder-mounted radar with freeway flow models, are in declining use. Cellular phone reports and highway patrol reporting have long been shown to be more accurate and timelier than methods that rely on point detectors, particularly since point detection devices require frequent maintenance and provide noisy and missing data on traffic volume and speed. At least two examples of incident detection based on AI methods can be highlighted. Both agencies expected that use of AI methods would improve their ability to react to incidents faster by detecting them sooner and in locations where traditional detection is lacking or where traffic levels are low (e.g., rural areas with limited cellular coverage).

Nevada and Florida Departments of Transportation

Both Nevada and Florida departments of transportation (DOT) use a proprietary software as a supplement for incident detection. The AI system fuses information from a variety of sources to detect and report suspected incidents.

In addition to the traditional sources which include radar and loop detectors, the AI system processes feeds from existing Nevada DOT (NDOT) and Florida DOT (FDOT) closed-circuit television (CCTV) cameras to identify incidents using AI (neural networks). This neural network is trained to recognize scenes that are "incidents" and "not incidents," as well as "incident may be likely to occur." In both cases, the application software was deployed in areas with good existing coverage of cameras and traditional point detection. Neither agency has used traditional software incident detection methods for some time due to the unreliability of such software and since highway patrol incident warnings have tended to outperform software detection methods in recent years. Both NDOT and FDOT have reported improvements in incident detection times by the AI system of up to 12 minutes faster than other input streams and reducing crashes by 17 percent by positioning highway patrol assets accordingly and providing advanced warning of downstream congested areas on dynamic message signs.

The system is provided as cloud-hosted proprietary software that is paid for as a subscription service. Both agencies plan to continue to expand the use of the system to more freeway coverage in their existing Districts (Las Vegas and Tampa), as well as expanding the deployment to other Districts in the State, particularly to rural areas where incident reporting tends to take much longer than in urbanized areas. Both agencies began the deployment as pilot projects with the software vendor providing the software in a testing configuration. NDOT and FDOT supplied the necessary data feeds and access to configuration databases with the AI software vendor doing most of the work. Both agencies expect to expand their deployment of the system to include areas where their traditional detection infrastructure is lacking (e.g., rural areas)

Iowa Department of Transportation

Iowa DOT has partnered with Iowa State University to develop an incident detection system that relies on AI (neural networks). Similar to the goals of NDOT and FDOT, Iowa's system is focused on improving incident detection time, particularly in rural areas where camera surveillance may be available, but highway patrol notifications may take an extended period to be received. Iowa DOT has named this system Traffic Incident Management Enabled by Large-data Innovations (TIMELI).[70] TIMELI uses NVIDIA Titan X graphics processing units and the open-source TensorFlow deep learning system to classify images from traffic surveillance cameras in near real time. The Iowa DOT TIMELI system monitors cameras from across the entire State and includes other data feeds such as incident reports, traffic congestion level, etc. The research project is being piloted now. According to the team, the AI technology and big data tools necessary for this size have only been available in the last three to five years. The system development and implementation were supported by a $1 million National Science Foundation grant secured by Iowa State in 2016.

In addition to the neural network incident-detection algorithms and supporting software, the TIMELI system includes information visualizations and data storage, processing, and archiving based on big data technologies, such as not only structured query language (NoSQL). The researchers have not yet to date publicly documented any quantitative improvements, but feedback from Iowa DOT TMC managers and staff has been extremely positive.[71] Most of the work has been done by researchers at Iowa State University with Iowa DOT staff providing access to databases and real-time data feeds. An overview video is available on YouTube.[72] Iowa DOT plans to continue expanding the use of TIMELI throughout the State.

ARTIFICIAL INTELLIGENCE FOR RAMP METERING

Traditional methods of ramp metering typically rely on loop detectors or shoulder-mounted radar detection to determine ramp metering rates at individual ramps. A few corridor ramp metering algorithms have also been implemented by State DOTs.

70 https://news.developer.nvidia.com/ai-system-helps-detect-and-manage-traffic-incidents/
71 https://www.news.iastate.edu/news/2017/03/22/timeli
72 https://www.youtube.com/watch?v=--C-vISrjZw

Fuzzy logic and neural network methods of various flavors have been applied to ramp metering for individual ramp control,[73, 74] and for corridor operations.[75] Fuzzy logic has seen success in the real world, with implementations at the California DOT (Caltrans) in Northern and Southern California and Washington State DOT (WSDOT).[76, 77] In these systems, individual ramps are configured with relatively simple fuzzy rules that determine to raise the metering rate when the freeway is uncongested and the ramp queue is lengthy and vice versa.

Washington State Department of Transportation

WSDOT has used fuzzy logic metering for more than 15 years. The initial implementation pilot project was led by the Washington State Transportation Center of the University of Washington in the mid-1990s. One of the benefits cited for the development of the fuzzy logic approach in the initial research was that only 5 percent of the code in the system was for the algorithm and 95 percent was for interfacing to the data inputs and providing metering outputs to the field controllers.[78] WSDOT chose this fuzzy logic method primarily because previous ramp metering algorithms using heuristics and flow models at that time required substantial code for estimation of the effects of various choices of ramp metering rates, and calibration of model parameters was particularly difficult. The fuzzy logic method has since been continued to be updated as computing technology has evolved from virtual access extension computers to modern servers and databases. The Washington State deployment of fuzzy logic metering currently extends to more than 200 ramps.

Evaluation studies date back to 1999 to 2000, where University of Washington found that fuzzy logic metering provided benefits in mainline efficiency by reducing both upstream and downstream occupancy at each ramp and did a far better job than local metering at maintaining reasonable ramp queues.[79]

WSDOT funded the development of the fuzzy logic ramp metering software through a grant to the University of Washington. The fuzzy logic software and code is the property of WSDOT and integrated directly into the WSDOT transportation management system (TMS). All new ramp meters utilize the fuzzy logic method for ramp metering; no other methods are considered.

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73 Sasaki, T., and T. Akiyama. Development of Fuzzy Traffic Control System on Urban Expressway. Proc., 5th IFAC/IFIP/IFORS International Conference in Transportation Systems, 1986, pp. 333–338.

74 Chen, L., A. May, and D. Auslander. Freeway Ramp Control Using Fuzzy Set Theory for Inexact Reasoning. Transportation Research Part A, Vol. 24, No. 1, 1990, pp. 15–25.

75 Sasaki, T., and T. Akiyama. Traffic Control Process of Expressway by Fuzzy Logic. Fuzzy Sets and Systems, Vol. 26, 1988, pp. 165–178.

76 https://dot.ca.gov/programs/traffic-operations/ramp-metering

77 https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/final-reports/ca18-2531-finalreport-a11y.pdf

78 https://www.wsdot.wa.gov/research/reports/fullreports/442.1.pdf

79 https://www.wsdot.wa.gov/research/reports/fullreports/481.2.pdf

Caltrans

Caltrans has recently deployed fuzzy logic ramp metering on the I-80 corridor Active Traffic Management (ATM) system in Oakland, CA. The Caltrans implementation follows the logic developed and implemented by WSDOT, but not the software. Caltrans District 4 decided to use the fuzzy logic method after an analysis of competing traditional ramp metering algorithms, including system-wide automatic ramp metering (SWARM). SWARM was developed for Caltrans in the early 1990s to coordinate ramp metering actions in a corridor, but was not found to be particularly effective, mostly due to the complexity required to accurately calibrate the flow model using data from inductive loop detectors that are (or were, at the time) unreliable.[80] Most ramp metering in California is currently locally traffic-responsive, using flow rates measured on the ramps and on the freeway using inductive loops, still prone to the same unreliability as the corridor-based methods such as SWARM. The use of Fuzzy logic was expected to reduce the complexity of algorithm configuration and improve the selection of appropriate ramp metering rates.

The fuzzy logic software was developed by their system provider and integrated directly into the ATM system. Costs specifically for implementation of the fuzzy logic software are not publicly available. Before and after analysis was not (or has not yet been) performed. According to the Caltrans 2017 ramp metering development plan, the fuzzy logic method is in consideration for statewide standardization, but it is not yet mandated to be used in all Districts.

CHATBOTS FOR NATURAL LANGUAGE QUESTION AND ANSWERING

For many years, 511 systems have used natural language processing (NLP) to understand a user's requested route. These systems historically have been limited in both their technical capability (understanding user phrases with background noise, i.e., while driving) and the phraseology expected from the user (bus stop identification numbers, freeway names and sections, etc.). Significant enhancements of NLP capabilities in digital assistants should be able to be leveraged in coming years. Metropolitan Transportation Commission (MTC) Bay Area 511 now has an Alexa skill to pass through requests for 511 information for the same phraseology that works with their interactive voice response (IVR) module.[81] Alexa skills are becoming popular with cities as part of 311 and community service information systems, one of many examples in John's Creek, GA, a suburb of Atlanta.[82]

Recently, Virginia Department of Transportation (VDOT) held a "hackathon" with more than 50 volunteer developers to leverage the VDOT open data application programming interfaces (API) for a variety of quick demonstration projects. One of the winners ("Talk DOT") was an Alexa skill to allow users to ask questions of the VDOT database as if they were manipulating the

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[80] Ahn, et al. Evaluating the benefits of SWARM Strategy in Portland, OR. Proceedings of the 86th Annual meeting of the Transportation Research Board. Washington, DC. 2007.

[81] https://www.amazon.com/Metropolitan-Transportation-Commission-511-Bay/dp/B06XCF91HK

[82] http://johnscreekga.granicus.com/DocumentViewer.php?file=johnscreekga_1e50d448064c523725c604c623c7eeae.pdf&view=1

VDOT Web interface.[83] Additional functions of AI-based assistants, such as smart home technology can easily be extended to TMC operations, such as voice-activated video wall configuration and other enhancements to traditional operations.

In 2018, the City of Surprise, AZ (a suburb of the Phoenix metro area) developed a Google Assistant interface to their adaptive traffic control system. The chatbot system allows the traffic engineer to query status data using voice commands through a Google Home speaker, Google Mini, as well as Google Assistant on any phone or computer. The system is implemented using Google's DialogFlow, Actions console, Firebase, and Microsoft Azure as illustrated in figure 15. Summary data on performance and field issues are uploaded from the adaptive system to Azure. The chatbot then is available for the user to query a data summary for the performance of an individual traffic signal or arterial for a time and date up to 1 year in the past. A "performance report" lists the Cycle time, Phase Utilization, and Arrivals on Green for a signal in a 30-minute window for a date and time. A "problems report" lists preemptions, detector failures, and communications quality for a signal or arterial.

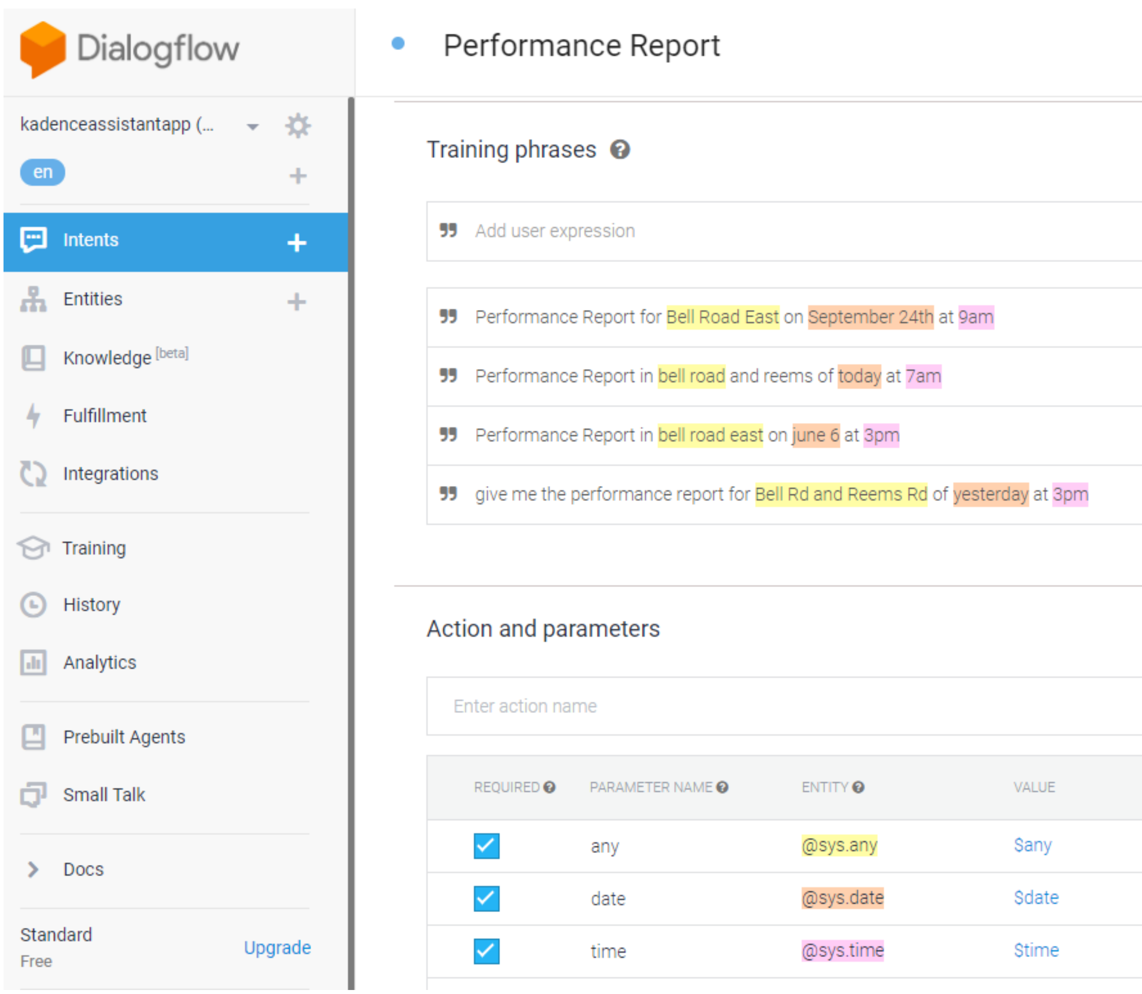

Figure 15. Screenshot. Google DialogFlow setup for the "performance report."
(Source: Federal Highway Administration.)

[83] https://devpost.com/software/talk-dot

The technical demo (alpha software) is intended to be expanded to retrieve reports and allow the user to send commands to the system, such as to change the adaptive system optimization strategy, via voice or text when the user is not in the TMC or near a computer with the TMS software. The City contracted with their system provider to develop the software. The development cost is not available to the public. Since the City is a small agency with limited staff, the traffic engineer envisions the AI application to save time when in the field and impress visitors to the TMC with voice activated video-wall management and other automated commands.

TRAFFIC PREDICTION AND TRAVELER INFORMATION

Neural networks, fuzzy logic, and Bayesian belief networks have been applied to the problem of short-term traffic prediction on freeways and arterials.[84, 85, 86, 87, 88, 89,90] Arterials are especially challenging because they require either imputed or explicit knowledge of traffic signal timing parameters.[91, 92] While most research has shown that such neural network models perform reasonably well with enough training (and accurate input data), their predictive power is

[84] See pages 38 to 41 of the 2012 TRB Circular (reference #27) for an exhaustive discussion of the short-term travel time and traffic conditions prediction problem on freeways and pages 50 to 63 for methods applied to "interrupted flow" facilities, i.e., arterials).

[85] https://en.wikipedia.org/wiki/Bayesian_network

[86] http://ascelibrary.org/doi/abs/10.1061/(ASCE)TE.1943-5436.0000816

[87] Huisken, G., and A. Coffa. Short-Term Congestion Prediction: Comparing Time Series with Neural Networks. Proc., Tenth International Conference on Road Transport Information and Control, No. 472, 2000.

[88] Huisken, G., and E. C. van Berkum. Comparative Analysis of Short-Range Travel Time Prediction Methods. Presented at 82nd Annual Meeting of the Transportation Research Board, Washington, D.C., 2003.

[89] Park, D., L. Rilett, and G. Han. Spectral Basis Neural Networks for Real-Time Travel Time Forecasting. Journal of Transportation Engineering, Vol. 125, No. 6, 1999, pp. 515–523.

[90] van Lint, J. W. C., S. P. Hoogendoorn, and H. J. van Zuylen. Freeway Travel Time Prediction with State–Space Neural Networks: Modeling State–Space Dynamics with Recurrent Neural Networks. In Transportation Research Record: Journal of the Transportation Research Board, No. 1811, Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 30–39.

[91] Lin, W. H., A. Kulkarni, and P. Mirchandani. Short-Term Arterial Travel Time Prediction for Advanced Traveler Information Systems. Journal of Intelligent Transportation Systems: Technology, Planning, and Operations, Vol. 8, No. 3, 2004, pp. 143–154.

[92] Liu, H., H. J. van Zuylen, H. van Lint, and M. Salomons. Predicting Urban Arterial Travel Time with State–Space Neural Networks and Kalman Filters. In Transportation Research Record: Journal of the Transportation Research Board, No. 1968, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 99–108.

typically limited to situations that were present in the training data and cannot easily be transferred to other locations and network topologies.[93,94]

Delaware DOT (DelDOT) recently received a $5 million grant from the advanced transportation and congestion management technologies deployment (ATCMTD) program of United States Department of Transportation (USDOT) to develop an AI TMS as part of the Advanced Transportation and Congestion Management Technologies Deployment Program. While much of the funding will go towards upgrading infrastructure including cameras and traffic controllers, a significant portion will fund the development of AI technologies for traffic prediction, incident detection, and automated traveler information dissemination. In partnership with Federal Highway Administration (FHWA) Turner-Fairbank Highway Research Center, DelDOT has piloted several AI methods in advance of the grant award. DelDOT's process for using AI at various stages in their TMC is shown in figure 16.

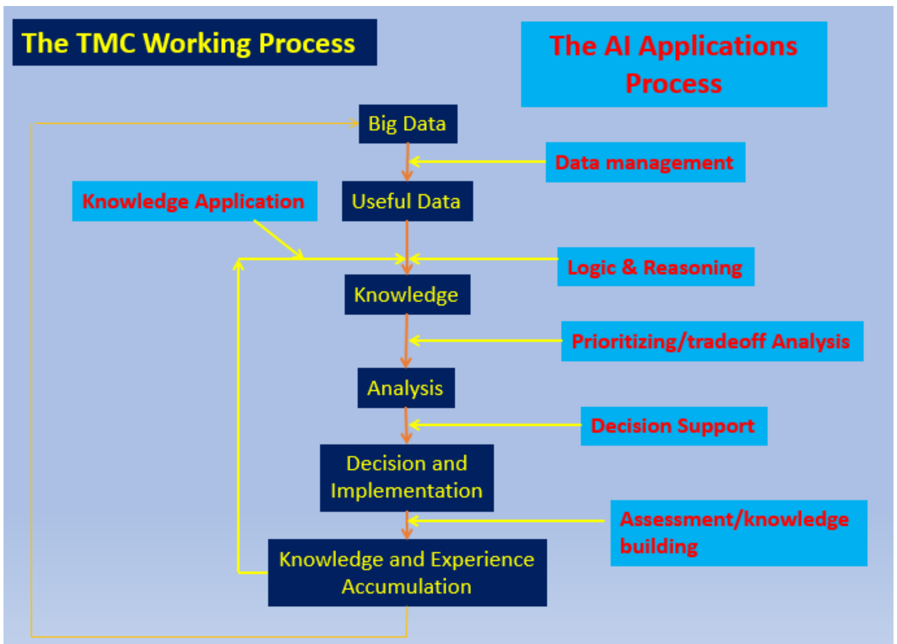

Figure 16. Chart. The Delaware Department of Transportation concept of how artificial intelligence can apply to the transportation management centers working process.
(Source: United States Department of Transportation.)

One component of the DelDOT AI strategy is to use reinforcement learning to train neural networks to manage traffic control systems as a "game" (e.g., chess) by predicting the impacts of certain traffic control actions and selecting the most effective control strategies. The pilot region/corridor where DelDOT has applied AI traffic prediction is shown in figure 17.

[93] Chen, H., and S. Grant-Muller. Use of Sequential Learning for Short-Term Traffic Flow Forecasting. Transportation Research Part C, Vol. 9, 2001, pp. 319–336.

[94] Ishak, S., and C. Alecsandru. Optimizing Traffic Prediction Performance of Neural Networks Under Various Topological, Input, and Traffic Condition Settings. Journal of Transportation Engineering, Vol. 130, No. 4, 2004, pp. 452–465.

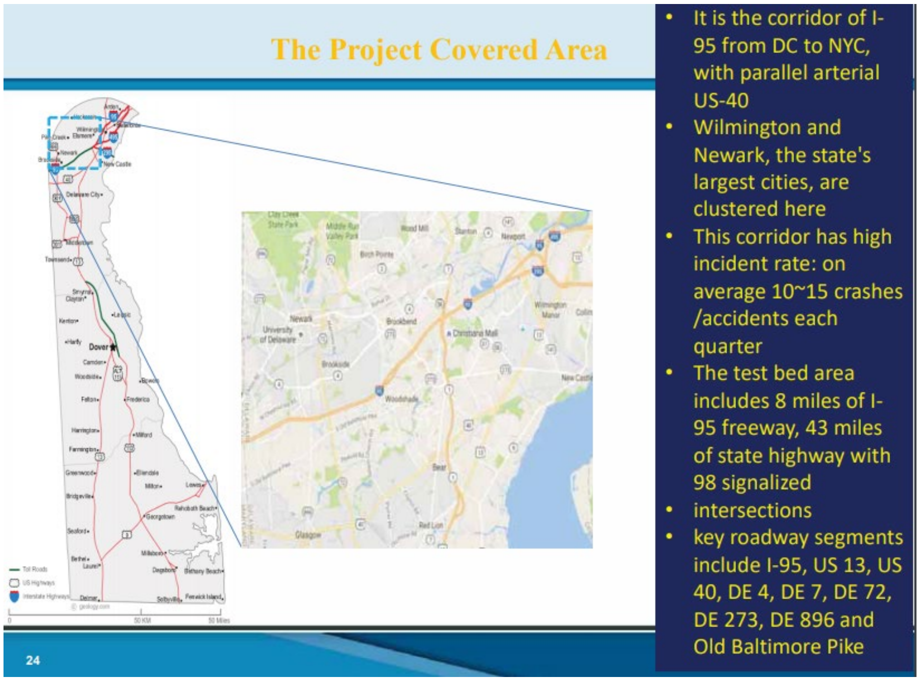

Figure 17. Photo. Network modeled by artificial intelligence in Delaware.
(Source: United States Department of Transportation.)

The pilot application of neural networks to this problem has already achieved the following objectives for assisting the TMC operators in prioritizing their workflow in the pilot corridor/region:

1. Seamlessly monitoring the network situation—reducing the major workload for TMC operators.
2. Alerting the operators to special situations (incidents).
3. Providing information on the suspected cause of the situation and the possible prioritized options to deal with the situation.
4. After the operator selects one specific option, the AI tool dynamically simulates the consequence of executing the option and predicts the time to resume normal operations and how traffic will evolve back to normal.
5. Evaluating and storing the results in the knowledge base for future use.

In addition to this, the pilot deployment includes another neural network model that detects incidents based on re-identification of vehicle signatures from one set of in-pavement loops to another. This concept is illustrated in figure 18.

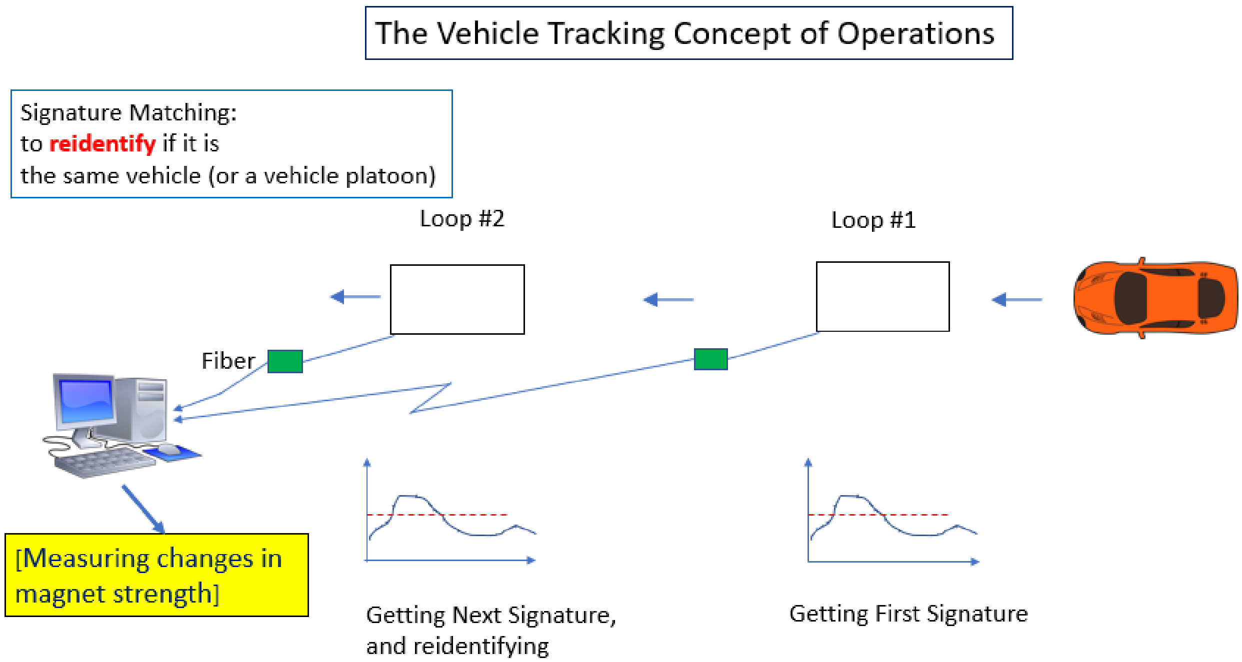

Figure 18. Diagram. Vehicle re-identification using inductive loop signatures matched by a neural network model.

(Source: United States Department of Transportation.)

UNMANNED AERIAL SYSTEMS USED BY STATE DEPARTMENTS OF TRANSPORTATION

Asset management is another important element of TSMO that continues to increase in importance. Long-standing asset management practices exist for pavements, bridges, and other transportation infrastructure. Light detection and ranging (LiDAR) technology and unmanned aerial systems (UAS) photography and video feeds are now enhancing how asset management and inspections are processed. The three-dimensional (3D) point cloud data and high-resolution video generated by UASs is overwhelming in content. Machine learning tools such as neural networks and other image processing algorithms are applied to 3D point clouds to extract information and features.[95]

As of March 2018, 35 of 50 U.S. State DOTs have a UAS program, with 20 of the 35 using UASs for daily operations and 15 in the research phase.[96] Most UASs have basic autonomous functions such as "return to base" and "hover here," but are still operated by a pilot and an observer or a pilot alone, depending on the application. UASs are most commonly used for photography, surveying, pavement inspection, daily traffic monitoring, and light pole inspections. Twenty-seven of the 35 State DOTs have added full-time staff to operate and maintain UAS fleets.

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95 http://www.sciencedirect.com/science/article/pii/S147403461630310X
96 https://csengineermag.com/35-state-dots-deploying-drones/

North Carolina DOT (NCDOT) and North Carolina Highway Patrol have researched the use of UASs to perform crash reconstruction data collection. In simulated testing of a staged head-on collision on a divided highway, use of three UASs reduced the time to perform the reconstruction activities from 2 hours to 30 minutes. NCDOT reported if the crash had occurred on I-95 at a busy time of day, the lost productivity impact of vehicles delayed by the lane closures would have been reduced from $12,900 to just $3,600.[97]

SUMMARY OF THIS CHAPTER

A variety of AI technologies have been deployed for TSMO applications. After reading this chapter, you should now be aware that several State and local DOTs have begun deploying neural network technologies for incident detection using video image analysis and traffic prediction. Fuzzy logic has been used by WSDOT for more than 20 years and Caltrans has begun deployment of fuzzy logic metering. DelDOT has piloted several AI applications for traffic congestion and incident prediction in partnership with USDOT. MTC and several other agencies have light integration of 511 with Alexa. Several arterial management agencies are piloting use of Google Assistant. More than 20 State DOTs have active UAS programs. Several DOTs are piloting use of automated vehicles for crash abatement. As AI technology continues to mature, the applications for AI in TSMO are likely to continue to expand. In the next chapter, guidelines for consideration of AI in TMCs and TMSs are provided.

[97] https://csengineermag.com/35-state-dots-deploying-drones/

CHAPTER 5. CONSIDERING ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN TRANSPORTATION PLANNING, DEPLOYMENT, AND OPERATIONS

Artificial intelligence (AI) and machine learning are elements of business intelligence (BI) strategies and technologies, which are used by enterprises for data analysis and information extraction. Traditional problems, functions, or actions that AI techniques can address include reasoning, knowledge representation, planning, learning, natural language processing (NLP) (and understanding), perception, and the ability to move and manipulate objects.[98] In each problem area, AI technologies are proving to have significant performance benefits versus other traditional mathematical modeling approaches. For example, the capabilities of digital assistants to understand human speech significantly outperforms the interactive voice response (IVR) technologies used in 511 systems over the past 20 years.

Various types of AI technologies could be used to help infrastructure owner-operators (IOO) for transportation systems management and operations (TSMO). For example, neural networks may help agencies improve incident detection time and identify anomalous activity, such as pedestrians or debris on a freeway; fuzzy logic may simplify the configuration of ramp metering systems; natural language question-and-answering systems may expand the abilities of TSMO staff to quickly obtain information from databases of facts and figures; and unmanned aerial systems (UAS), both on the ground and in the air, will likely augment human workers in a variety of ways. The selection of AI technologies is dependent on the particular problem at hand.

As discussed in chapter 3, the development of AI technologies is currently becoming commercialized. AI development platforms are now available from major software providers such as Google, Amazon, and Microsoft as well as hundreds of other niche and generalized companies, including companies focused solely on the transportation management market. Each of the major technology providers continue to improve the capabilities of their suite of software modules for AI to make the development of applications easier and more accessible to users without deep and extensive expertise in machine learning. At the time of this writing; however, it is still the case that AI applications for TSMO will require extensive involvement from experts in AI, software development, and database management. Procurement of AI applications is currently a complex undertaking, which may range from purchasing a software package from a vendor to developing in-house applications using cooperative University resources for research and development.

In chapter 4, a few examples of existing applications of AI to TSMO problems were presented. These examples illustrate some of the potential for AI in TSMO, particularly in imagery analysis for incident detection and the automation of transportation management centers' (TMC) functions through digital assistants. Aside from the fuzzy logic methods that have been used for ramp metering by Washington State Department of Transportation (DOT) for an extended period, most AI application examples are exploratory and have been recently deployed. Most applications have seen significant performance improvements, although benefit/cost analysis has not been completed and documented.

98 https://en.wikipedia.org/wiki/Artificial_intelligence

In this chapter, you will discover issues that should be considered in planning, deployment, and operations of AI technologies for the TMC, and transportation management systems (TMS). This includes the identification of:

- Clear objectives to be addressed with AI.
- Systems and technology that are required for different types of AI applications.
- Changes or enhancements to staffing and organization may be needed for deployment of AI.
- Business processes that may need to change.
- Types of collaborations that can be made with other DOT divisions or other State and local agencies to reduce cost and complexity of deploying AI applications.

This chapter is organized around a subset of the topical areas of the capability maturity model for TSMO:

- Systems and technology.
- Staffing and organization.
- Business processes.
- Collaboration.[99, 100]

Each of these subareas will be discussed and checklists of questions and issues will be provided for your use in generating an AI concept of operations.

There are many issues that will be common in any AI program development, including systems engineering, deployment, operations, and maintenance and new capabilities.

Infrastructure owners and operators will need to employ systems engineering of new concepts and applications in considering:

- The deficiencies of current TSMO activities are to be addressed by use of AI systems.
- The improvements gained by using AI systems versus traditional systems.
- The maturity of AI technology to support a specific application.
- The prototype status of AI tools and technologies and consensus on practical “day one” applications.
- The appropriate software systems, databases, and computing resources.
- The integration of new systems and software with legacy systems and software.
- The capabilities of IOOs to adjust processes to appropriately take advantage of new functions.
- The use of AI technologies beyond TSMO and collaborations with other DOT departments or other departments within a State or local agency.

[99] https://en.wikipedia.org/wiki/Capability_Maturity_Model
[100] http://www.trb.org/Publications/Blurbs/165285.aspx

The development, deployment, operations, and maintenance of new AI systems may place significant burdens on agency capabilities in the areas of:

- Policy development and compliance with legal requirements regarding security and privacy.
- Management and integration of AI software that requires highly skilled personnel in short supply.
- Funding constraints.
- Development of new business processes required for AI applications and integration of AI into existing processes.
- Management new types of data and volumes of data with modern tools and technologies.
- Measurement of AI application deployment performance.

Some AI applications may involve coordination and collaboration with local IOOs, metropolitan planning organizations, and coalitions. There is also a likely role for private service providers to collect and process data and implement solutions on behalf of the agency. This implies the need for capabilities in the areas of:

- Developing guidelines and collaborative agreements across regions.
- Establishing new forms of public-private partnerships.
- Considering partnerships and data packaging from third-party commercial providers.
- Developing and retaining specialized staff and knowledgeable management.
- Developing an appropriate organizational framework for coordination and allocation of authority and responsibility.

SYSTEMS AND TECHNOLOGY

AI applications for TSMO will be based on software, databases, and information technology. Many issues will be needed to be considered in deploying AI. As detailed in chapter 3, most AI applications will include some level of consideration of the Cloud. This includes Cloud data storage, Cloud computing, and leveraging Cloud software services. DOTs range widely in information technology (IT) policies and procedures when considering Cloud applications and technology. Partnering with the IT department early in the project development phase will be an important element of success in developing and deploying AI applications.

The following issues are important to consider in software, databases, and IT:

✓ What operating systems do we use? Linux, Mac, Windows?	☐
✓ Can we consider other operating systems than those we do not currently use?	☐
✓ Do we have experience with other operating systems used by a particular AI technology or system?	☐
✓ What databases do we use? Oracle, structured query language (SQL), NoSQL, or something else?	☐
✓ Can we consider other databases than those we do not currently use?	☐

✓	Do we have experience with other databases used by the AI technology or system?	☐
✓	How do we deploy databases and can existing clusters or virtual machines be used for AI applications?	☐
✓	What other on-premise computing resources will be required? Do we have adequate space for new hardware in existing computing and data centers?	☐
✓	Do we have experience with the many AI applications that require merging data from multiple sources and formats?	☐
✓	What database and operating system technologies do our current TMSs rely on?	☐
✓	How will we integrate our legacy TMS with new AI software?	☐
✓	Can we replace or integrate certain elements of AI software with legacy TMS systems?	☐
✓	What application programming interfaces (API) do our current legacy TMSs have? If APIs do not currently exist, can they be developed?	☐
✓	What API standards do we support? Can the AI software or systems use these API standards, or will new integration be required?	☐
✓	How much of the system will be deployed on-premise versus in the Cloud?	☐
✓	Can we use public Cloud hosting or do we need a private Cloud or hybrid Cloud environment?	☐
✓	What sensitivities to data protection and personally identifiable information does use of the Cloud for AI applications present? Do we know what requirements or organizational policies are already in-place for handling Cloud applications and data storage? *(See note below)*	☐
✓	Are their cybersecurity issues to be addressed when using AI applications? What vulnerabilities or sensitivities may arise by use of AI software?	☐
✓	What policies or procedures are necessary for use of open-source AI software?	☐
✓	What policies or procedures are necessary for use of vendor proprietary or trade secret AI software?	☐
✓	What procurement models and methods of procurements can we use and have experience with? Does our organization preclude use of any procurement method?	☐
✓	Can the AI software and supporting databases and systems be procured as SaaS? PaaS? IaaS? DaaS? Traditional licensing?	☐
✓	Do we understand how software maintenance, updates, upgrades, and modifications will be handled?	☐
✓	Do our current vendors of TMS and related systems have experience with AI applications?	☐

Note: Commonwealth of Virginia, Information Technology Resource Management (ITRM), Cloud-Based Hosting Services for IT Solutions Policy: https://www.vita.virginia.gov/media/vitavirginiagov/it-governance/docs/Cloud_Based_Hosting_Services_IT_Solutions_Policy_EA300_FINAL.pdf.

STAFFING AND ORGANIZATION

Use of AI applications will require technical capabilities that likely exceed existing level of in-house expertise in most IOOs. Similarly, organizational decisions will be required to determine which department(s) or agency staff will be involved in the project and responsible for success.

✓ Do we have a champion for the development and deployment of AI systems?	☐
✓ Is this champion in our organization?	☐
✓ Does our organization embrace technology and innovation? Is there a commitment from leadership to advance technology?	☐
✓ Are there tangible steps to take to promote a culture that embraces technology?	☐
✓ What groups or divisions will have primary involvement in deploying, operating, or maintaining AI applications and related infrastructure?	☐
✓ Which division of the organization will be responsible for success? IT? TSMO? Geographic information systems (GIS)? Other?	☐
✓ Can we partner with other divisions or groups within our organization that are also interested in developing and deploying AI technologies?	☐
✓ Are there other departments or partner agencies that are already using AI in some fashion that can help us? How can we engage those partners?	☐
✓ What basic and advanced skills are needed, and does our staff have these skills?	☐
✓ What specific technical areas do we have that can support deployment of AI technologies? a) System engineering. b) AI Design. c) AI Deployment/Integration. d) Data management. e) Operations. f) Maintenance. g) Analytics.	☐
✓ Is there flexibility to acquire agency staff with these skill sets (i.e., redefine roles, expand technical staff groups)? What retention issues might we experience with highly skilled staff?	☐
✓ Do we have a mechanism to obtain these skills if they cannot be addressed by current staff or roles (i.e., contract/outsource, training)?	☐
✓ Are there any operational or policy limitations on our agency deploying AI applications? How do we removed such barriers if they exist?	☐
✓ Do we have significant understanding or are we are hearing about peer agency programs and experiences, national trends, and AI technologies?	☐
✓ What training will staff need to develop, deploy, operate, and maintain AI systems?	☐
✓ Will there be a commitment from agency leadership to continue with AI systems?	☐

BUSINESS PROCESSES

The introduction of AI applications and pilots brings the identification of requirements for planning, scheduling, budgeting, and project development. The introduction of AI technologies will require processes for data collection, exchange, and action. Business processes for AI applications are especially important if the application area is not a TSMO area an agency currently uses, and therefore, has not already initiated efforts to advance business processes through TSMO program planning or related work. Agencies may need new roles at the IOO, such as database and AI technology specialists. For most AI applications, an agency will need an institutionalized approach to cybersecurity and privacy. In the short term, IOOs may have significant technical challenges. In the long term, it is anticipated that these challenges will evolve towards standards and best practices.

✓ Have we developed the business case for an AI application or program?	☐
✓ Have we engaged with partner agencies that have piloted or used AI in a similar manner?	☐
✓ Have we documented the relationships between TSMO processes and new AI capabilities?	☐
✓ Have we documented a communications strategy for public and internal benefits of business process standardization using AI?	☐
✓ Have we developed an interdepartmental consensus framework for policy and planning for AI?	☐
✓ Have we documented which AI applications and functions will provide benefits to our specific regional issues?	☐
✓ Have we identified what the benefits will be? a) Reduction in process steps. b) Reduction of time for a human to complete an activity. c) Improvement in timeliness of actions. d) Reduction in complexity of processes. e) Improvement in quality of solution. f) Improvements in traditional metrics (travel time, congestion, delay, customer satisfaction, etc.).	☐
✓ Have we developed a plan to address regional processes and relationships among partner agencies for more holistic deployment of AI applications?	☐
✓ Have we developed a plan to secure the costs and resources will be required for implementation of AI technologies?	☐
✓ Have we gained agency buy-in for how these costs and resources will be borne?	☐
✓ Have we developed a plan for security and privacy management of AI applications and data?	☐
✓ Have we developed a plan for implementation of the concept of operations? Do we understand what an AI application will do, and what it will not do?	☐

✓ Have we developed a plan form implementation of the business processes related to a pilot deployment(s)?	☐
✓ Have we identified roles and responsibilities within and among agency partners for implementation of the business processes?	☐
✓ Have we considered the implications of potentially having an AI make decisions on behalf of the agency without interaction with staff?	☐
✓ Will we require the AI to only make recommendations and not implement decisions?	☐

COLLABORATION WITH OTHER DEPARTMENTS AND AGENCIES

AI applications and software/hardware tools are likely applicable to many other organizational groups, departments, and partner agencies. Given the experimental and cutting-edge nature of AI technology, collaboration may be beneficial to share costs, expertise, and responsibilities.

✓ Is there regional or interdepartmental interest or established goals that will be achieved through AI applications? Are multiple agencies or departments in my agency interested in advancing AI capabilities?	☐
✓ Have potential roles and responsibilities been identified for implementing or piloting AI capabilities?	☐
✓ Is there a forum for partner agencies or departments to collaborate/discuss/obtain consensus on potential AI applications?	☐
✓ Are there opportunities to leverage existing processes among agencies (business processes, planning, procurement, system engineering, and operations) to initiate AI capabilities?	☐
✓ Are there other departments or partner agencies that have experience with AI applications already? How can they be engaged?	☐
✓ Do some partner agencies have fewer barriers to certain processes? How might this influence planning for AI applications?	☐
✓ Are there departmental processes that would need to be factored in to piloting AI capabilities (i.e., Transportation Improvement Plan, programming and budgeting cycles, and flexibility to fund near-term improvements)?	☐
✓ Are there partner agencies or departments with staff who have skill sets that would align with AI capabilities? GIS? IT? Surveying? Asset management? Maintenance?	☐
✓ How aligned are partner agency missions with the TSMO mission with respect to AI applications? Is there a consistent interest and leadership support among partner agencies or departments?	☐
✓ How already involved are my existing private sector vendors, suppliers, and consultants in AI initiatives? Are there barriers to engaging additional private sector vendors, suppliers, or consultants in some capacity as part of an AI pilot? What are those barriers?	☐

SUMMARY

The previous section listed important questions to answer or address when embarking on the development of AI applications for TSMO. Identifying answers to these basic questions will better prepare transportation agencies for the potential impacts of AI on operational activities, resources, system needs, and decisionmaking. AI technologies are making major headway in commercial software systems, particularly for imagery analysis, pattern recognition and classification, consumer services, such as Google Assistant and Alexa, and automated vehicles on the ground and the air. Leveraging these technologies holds promise for improving TSMO activities.

Determining how to start in AI applications for TSMO will be unique to your organization. As is true with any TSMO activity, the basis for improvement of any activity with AI has three basic components:

1. A supporting institutional framework, policies, and appetite.
2. Processes, staff, and technology that support the program.
3. The implementation of the system itself.

The foundation of any successful program is first the institutional framework to support the activity. In the context of AI applications, this will require developing the necessary organizational structure and functions for TSMO. After these enabling actions, the business processes for using AI technologies for TSMO practices will follow more readily and be more effective due to a strong foundation in business processes. These processes will, in turn, ensure that the AI program functions at a high level initially, and continues to adapt and improve as AI technology advances and new applications and functions are identified.

Developing these foundational elements is important and answering the questions in the chapter will help to identify where the strengths and weaknesses lie. It is important to keep in mind in any technology deployment that some of the dimensions are inherently more difficult to deal with than others, yet they all must be addressed to move forward. Failing to consider issues related to staffing and organization, for example, may result in your AI project being a pilot that is never integrated into the main TSMO operation.

A Holistic and Programmatic Approach

The application of AI technologies could be a next step in the provision of mobility and safety services that improve congestion and safety. However, not unlike TSMO strategies, AI applications will likely require new planning and programming approaches, potentially with the need for collaboration with local agencies and other departments of the DOT or agencies outside of the DOT. Agencies might consider coordinating AI application program planning with TSMO program planning. As detailed in previous chapters, the development of AI technologies continues to evolve, and the current state of the art is not yet “plug and play.”

Specific AI applications such as fuzzy logic ramp metering and incident detection through closed-circuit television (CCTV) analysis may possibly be considered independently of other programs or agencies. Technologies like automated UASs and digital assistant natural language processing services may benefit from coordination among other programs or agencies. In many long-range planning processes, an "unconstrained" future is envisioned for the planning horizon. That is, if funding was not an issue, what would be built and developed to meet our regional mobility, safety, and environmental goals? How are AI technologies a fundamental element of this future?

After considering an unconstrained future, realistic plans can be considered in the context of funds available for software and hardware procurement, equipment deployment, and operations practices. A similar approach might be applied to AI program planning. A holistic program plan may be developed considering many potential applications and pared back to consider what might be accomplished with more realistic budgets and resources.

Suggestions for How to Approach the Development of Artificial Intelligence Applications

Where to start? Agencies in the early planning stages might take the following steps:

1. Convene an interdepartmental workshop to educate stakeholders, partners, and potential partners on AI and brainstorm potential applications and synergies.
2. Discuss priorities, opportunities, and barriers to AI applications in each of the TSMO areas.
3. Determine a short-list of high-priority applications and a longer list of secondary-priority functions that address regional issues, challenges, and goals. While many goals are generic, tailoring the AI strategy to regional hot-button issues is typically helpful in gaining broader buy-in from decisionmakers and associated agency departments.
4. Review the list of general and detailed questions in this chapter and consider the responses of your organization to each.
5. Develop a project plan to implement the actions.

The results of the self-assessment process will likely identify a significant list of actions. The next step will be to prioritize the completion of those actions to achieve the desired outcomes within a reasonable schedule. In many program planning activities, it may be helpful to link the completion of key milestones with other related activities. Could the AI technologies be linked to the opening of a new stadium? Reconstruction of a bridge or major interchange? Roll-out of other programs such as managed lanes, Vehicle to Infrastructure (V2I), or Infrastructure to Vehicle (I2V)? Working backwards from a common deadline for other facilities or programs may motivate actions and reveal the schedule for activities that have dependencies on the development of AI software for TSMO.

Relationships of Artificial Intelligence Program Planning with Connected and Automated Vehicles

In 2019, agency planning for connected and automated vehicles is another popular topic for IOOs. The topic of connected and automated vehicles is quite likely to be a point of discussion in AI technology workshops. While most connected and automated vehicles in development by private companies today have some elements of AI, synergies of V2I and I2V services with AI at the TMC may become important in the future. For example, the sheer volume of data that is returned to the TMC by connected vehicles will likely require AI technologies to be effectively processed. Similarly, AI technologies may be helpful in personalizing traveler information back to connected vehicles by fusing agency data (work zones, crashes, traffic congestion, etc.) with vehicle data. Many other synergies will likely be identified in the future as TSMO agencies gain more experience with V2I, I2V, and AI. While there are still many uncertainties regarding timing and availability of both connected and automated vehicles, both technologies and AI are likely to be a significant component of the transportation landscape over the next decade. IOOs considering connected and automated vehicle program plans may find value in considering implications for AI at the TMC and in TMS at the same time.

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