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Artificial Intelligence and Planning Practice

By David Wasserman, AICP, and Michael Flaxman, PHD

The term "artificial intelligence" (AI) conjures images of autonomous vehicles maneuvering through streets, smartphone assistants that answer your questions, or androids exploring final frontiers.

At a basic level, however, AI can be understood as the multidisciplinary endeavor to approximate human reasoning with computation. For planners, it represents an emerging toolbox that enables a range of new capabilities—from the scalable digitization of physical infrastructure to tools that can help planners synthesize and summarize public feedback (Figure 1).

The rapid advancement and integration of such techniques into daily life are increasingly influencing planning practice and our communities at large. Whether AI primarily benefits entire communities or narrow interests, though, depends on planners' abilities to engage with the challenges and opportunities surrounding its civic applications. Naively applied, these technologies can automate discrimination, create unaccountable processes, and create a false certainty about what the future holds.

This *PAS Memo* intends to equip planners with an understanding of AI concepts and their potential implications.

Figure 1. AI offers planners an emerging toolbox enabling a range of new capabilities, including the transformation of raw imagery and data feeds into living digital views of our world (David Wasserman)

Additionally, it will discuss important considerations regarding AI applications and their roles in larger trends connected to digital governance and civic data in planning.

Wide availability of this technology is still very new, but it is powerful and fast moving. Planners have a responsibility to understand the implications of the technologies they choose to deploy, and, with understanding, they can help to ensure that these technologies are used responsibly.

Background

The field of AI research began in the 1950s. Early investigations included a paper by Alan Turing, the British mathematician considered the father of computer science, exploring whether computers can think, as well as a 1956 U.S. Department of Defense-sponsored conference at which the term "artificial intelligence" was coined (McCarthy 2012). The field kicked off in earnest, however, when the first microprocessors were developed in the 1970s.

One of the first applications of AI was symbolic AI, such as expert systems, which sought to encode the decision-making capacity of experts in complex sets of handcrafted rules. This required heavy involvement from industry experts, and low returns led to a series of "AI winters" in which research and funding in the field withered for decades (McCarthy 2012).

Everything changed in the early 2010s. New advancements in AI were driven by three intersecting factors:

- **Advent of robust techniques.** "Deep learning" kindled a renaissance in the subfield of machine learning, the study of algorithms that improve with experience (Council of Europe 2020; Singh 2019). Deep learning provided a generalized set of machine-learning algorithms loosely inspired by neurons in the brain. This enabled a rapid, extreme improvement in complex, multidimensional pattern-matching—allowing computers to find patterns in complex and multidimensional data such as images and audio (Singh 2019).

- **The data revolution.** For machines to learn from experience, many known methods require access to big datasets to "train" them on. Social media, the increasing maturity of the Internet, and the digitalization of the human experience contributed to availability of examples for model training (Council of Europe 2020; Singh 2019).
- **Improvements in computing hardware.** The same graphics processing units (GPUs) that enabled video games to become an American pastime massively reduced training time for huge datasets. Researchers' experiments could take minutes, rather than weeks, by leveraging modern GPUs and advanced cloud computing infrastructure to drastically increase parallel processing capabilities (Council of Europe 2020; Singh 2019).

Combined, these advances enabled computers to learn by example, creating a new computer programming paradigm.

Learning by Example

When software developers write a program, their code processes input data to create an output using human-crafted instructions. Machine learning reverses this logic: it combines input and output data to create a program.

Machine learning provides a set of automated methods that do not require substantive domain knowledge other than that encapsulated in the training examples. In this sense, it is conceptually more akin to statistics than to conventional coding. However, there are two critical differences.

First, unlike statistics, machine-learning methods are not limited to highly structured numerical data. They have robust performance when working with complex multimedia files including images, video, and audio (ITF 2019; Singh 2019; Crawford 2021) and can accurately relate examples from those formats to arbitrary output concepts (Ding 2020; Singh 2019).

The second difference is in the volume of data required. Statistics can typically be run on dozens to hundreds of samples; complex machine-learning models often require millions. This, in turn, implies that most models must initially be trained somewhere by someone with access to enormous quantities of training data and thus require large computational capabilities. While cloud computing allows even small planning departments access to high-performance computing, this last requirement is often a binding constraint.

A Digital Foundation

The "data hungriness" of machine-learning models is the perhaps the biggest impediment to their use in planning. In some cases, training data can be gathered from routinely digitized data such as administrative records or synthesized in game engines used in the video game industry (Andrews 2021). In others, though, human hand-annotation is required, which sharply limits scale. While there are innovative techniques that can reduce the data required to develop these models, data remains central to how AI works (Jain et al. 2011; Crawford 2021).

Many communities still use analog steps (e.g., physical paper) for key planning processes (e.g., building permitting).

Important Terminology

- *Algorithm* – a set of specific steps to perform a well-specified task. Algorithms typically take in some input and then apply a process to create an output.
- *Algorithmic bias* – systematic and repeatable errors in a computer system that create unfair outcomes, typically privileging one group of users over others.
- *Artificial intelligence* – a simulation of human intelligence and reasoning.
- *Civic analytics* – the application of advanced data mining, modeling, and analysis techniques to enable data-informed and evidence-based decision-making in urban and regional operations, policy, and planning.
- *Computer vision* – a field that focuses on how computers can gain high-level insights from digital images or videos.
- *Digitization* – the conversion of data and documents into a computer-readable format.
- *Digitalization* – the conversion of analog processes to digital experiences. This can make a process more transparent, accessible, and convenient while enabling easier reporting and analysis of incoming information to guide decision-making.
- *Digital twin* – a digital representation of the built environment or system. A ***smart city digital twin*** is continuously updated with real-time data and analytics on interactions between humans, infrastructure, and technology to create a living digital representation of a city.
- *Machine learning* – algorithms based on applied statistical models that can learn without following explicit instructions. These base decisions on inferences drawn from patterns in data.
- *Natural language processing* – a subfield of linguistics, computer science, and artificial intelligence that that focuses on how computers can derive understanding from natural language.
- *Personally identifiable information* – any information that can be used to distinguish or trace an individual's identity, either alone or linked with other correlative datasets. This can include identifiers such as names and social security numbers, but it can also include mobile GPS data or sequenced images.
- *Training data* – labeled datasets input to supervised machine-learning models to teach them relationships they can infer from the data. A prototypical example is a collection of images labeled by what they contain in a separate spreadsheet. The quantity, quality, and degree of representation in these datasets has important implications for how the models created from it perform in real world applications and the degree of bias they operate with.
- *Urban informatics* – the study of urban phenomena through an evidence-based framework of urban sensing, data mining and integration, modeling and analysis, and visualization to advance methods in computational sciences and address urban and regional challenges.

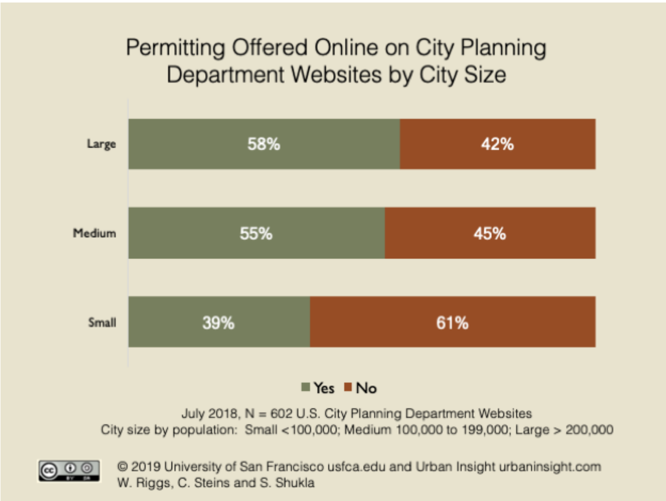


Figure 2. Online permitting by city size (Riggs et al. 2019)

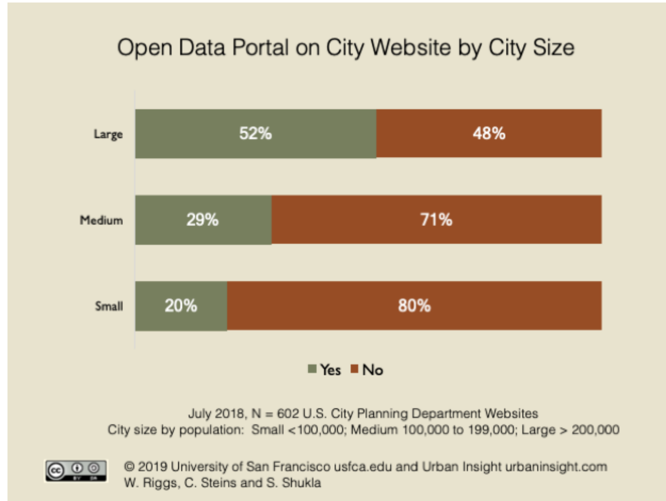


Figure 3. Open data portals on city website by city size (Riggs et al. 2019)

Data gathered in this way can't be directly used with AI tools until it has been digitized (DeAngelis et al. 2022; Miller 2021). Local governments may be able to obtain digitized data from vendors and other sources, but they still need the capacity to maintain and leverage it to inform decision-making. Before cities can apply AI to specific areas of planning practice, then, they typically need foundational investments in data infrastructure to build the institutional capacity to manage it (Hurtado et al. 2021; Kontokosta 2018).

Some work in this area has already been done through the digitization of planning-relevant data and digitalization of its processes and systems. What began with GIS (Klosterman 1999) has evolved into a rich ecosystem of web maps, data vendors, open data portals, and online engagement systems that hint at entirely new governance models in planning (Bayat and Kawalek 2021; Hurtado et al. 2021).

However, progress has been uneven. The 2019 Technology Benchmarking survey conducted by the University of San Francisco and Urban Insights of 600 cities found that all surveyed planning departments now have websites, indicating progress in providing information, but other components of the survey suggest a slower pace of digitalization in the planning process. For example, 53 percent of surveyed cities do not provide online permitting (Figure 2), and 72 percent have no open data portal on their city websites (Figure 3) (Riggs et al. 2019).

Consequently, much data related to the planning process is hard to access, siloed, or not being collected at all (Dimina 2019; Riggs et al. 2019; Noardo et al. 2022). For example, many cities store data as PDFs, which are easy for humans to read—but not computers. Most algorithmic tools can't use this data unless it is processed into a form they can read, like a database or text formats like HTML/XML (Noardo et al. 2022).

As data is central to AI, planning digitalization is an ongoing process that is a necessary precursor to realizing value from AI (OECD 2019; DeAngelis et al. 2022; Miller 2021). And investments in digitalization can also make "front desk" interactions with the public smoother and more user focused (DeAngelis et al. 2022). Paper permit submittals increase friction, attending meetings in person can be inconvenient, and reviewing plans in a static PDF is not engaging. In the long term, planning departments' inability to reduce these transaction costs by digitalizing their processes can erode public support for planning and the perception of its value (Zucker 2007).

The COVID-19 pandemic has pushed many agencies and organizations to accelerate digital governance initiatives. Even so, process digitalization is a challenge for the planning profession and public-sector governance at large. Investments in planning's responsiveness are effectively investments in community trust. Movement towards digital governance can improve planners' abilities to leverage emerging technologies to better serve their communities (Zucker 2007; DeAngelis et al. 2022). As emphasized throughout PAS Report 599, ***Smart Cities: Integrating Technology, Community, and Nature***, planners must adjust planning processes to today's digital environment and add new tools, relevant skills, and knowledge to their repertoires, both to ensure that their communities can benefit from digital technologies as well as to maintain the planning profession's relevance in an era of digital transformation (Hurtado et al. 2021; DeAngelis et al. 2022).

With the advent of the data revolution and wider deployment of sensors into our built environment, the growing field of civic analytics offers higher expectations and more opportunities to use data to address challenges in urban and regional operations, policy, and planning (Figure 4, p. 4) (Kontokosta 2018; Tomer 2019). These changes in data systems and new policy challenges have prompted cities to invest in cross-agency data sharing, mandate open data, and identify new roles in local government, such as chief data officer (Kontokosta 2018; OECD 2019). Additionally, governments are increasingly finding uses for emerging smart city solutions, civic software, and big data providers (Kontokosta 2018; Bayat and Kawelek 2021).

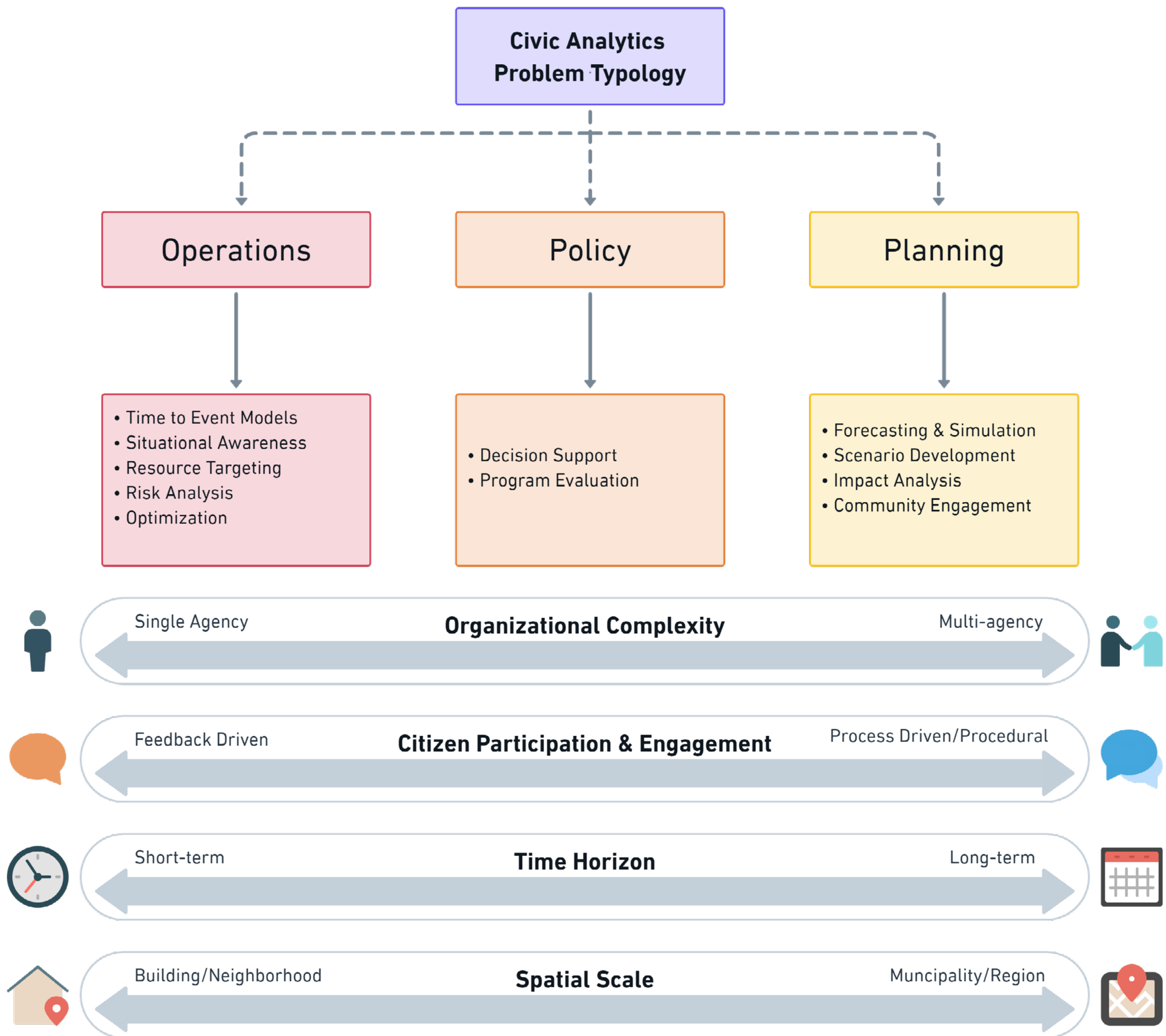


Figure 4. Civic analytics can assist with a broad spectrum of challenges within operations, policy, and planning for cities and regions (adapted from Kontokosta 2018).

Data's role in decision-making is likely to grow. Planners will benefit from an increased awareness of its potential applications, what gaps exist in their available data, as well as how to share, distribute, license, and manage it.

AI Applications for Planning Practice

These advancements in computer science, machine learning, and digitalization are creating an emerging AI toolbox that can extend planners' capabilities and complement their skillsets. AI can help planners improve data collection, forecast alternative futures, inform decision-making, and accelerate creative design processes.

Digitization of Infrastructure and Assets

Inventories of the built environment enable planners to understand the state of existing infrastructure relative to the needs of their communities (Wasserman 2020; Yigitcanlar et al. 2020). Planners typically inventory the built environment with parcel data, manual aerial reviews, and field data collection.

While some information, such as land cover or vegetation health, can be derived from remote sensing's automated data extraction techniques, more detailed components of the built environment were once difficult to automatically digitize. Advances in computer vision have enabled new techniques that can transform high-resolution aerial imagery directly into geospatial data, which can reduce costs and potential errors common in the tedious work traditionally required to digitize community assets.

The geospatial data and services company EarthDefine applied advances in remote sensing to generate a one-meter resolution tree canopy database that can be used in citywide comparisons of tree canopy at the street level (Figure 5, p. 5).

For comparison, the U.S. Forest Service produces a 30-meter tree canopy dataset whose resolution is not sufficient for urban tree canopy inventories. EarthDefine donated this data to American Forests to generate the Tree Equity Score database, which summarizes canopy cover at the census block group level to help determine inequitable distributions of tree cover within urbanized areas (American Forests 2021).

This type of extraction of data from aerial imagery can generate digital inventories of streets and other public works. For example, in California, Contra Costa County Public Works worked with earth image digitization company Ecopia to digitize the public rights-of-way across large parts of the county (Figure 6, p. 6). This transformed recent imagery into a geospatial cross-sectional database representing every lane, median, sidewalk, and crosswalk and their associated widths (Ecopia 2021).

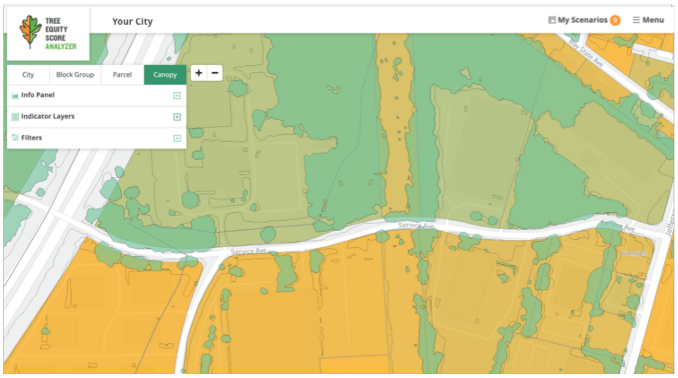


Figure 5. EarthDefine's one-meter resolution tree canopy database used by American Forests to generate the Tree Equity Score database (American Forests)

Data Standards, Open Codes, and Accessibility

When Google Maps was introduced in 2005, it shifted expectations of how we get from point A to point B (Reid 2020). Soon after its release, Portland, Oregon's TriMet collaborated with Google to identify how to represent transit systems and schedules in routing and trip planning. This collaboration ultimately culminated in the development of a new data exchange format—the General Transit Feed Specification (GTFS). Many transit agencies now publish GTFS data, which software providers can use to integrate transit service and schedules into routing, mapping, and other software services (McHugh 2013).

The story of GTFS illustrates how the public and private sectors can forge partnerships and develop data standards that can enhance public services at scale. GTFS enabled the creation of entirely new software, tools, and data ecosystems that enriched our understanding of transit (McHugh 2013).

Standards like GTFS allow private-sector software development to scale, reducing costs and market risks. For the public sector, data standards can help planning professionals build a shared understanding of their communities through more robust cross-regional research and enhance public services by establishing an agreed upon "data lexicon" that can be used to curate technological solutions (PIA 2021; McHugh 2013; Noardo et al. 2022). In permitting and agency operations, planning standards can be used to facilitate smoother transactions with users and the public, while on the back end they can be used to construct planning scenarios or provide consistent data across regions that can be used to train machine-learning models. And when software tools are based on standard data formats, they are more accessible to smaller communities—instead of needing to create a new tool to solve a common problem, communities can publish their own data in the same format to benefit from the work that has already been done.

What can planners do to improve this situation? Some useful principles have been developed by the Planning Institute of Australia (PIA):

Planning however is work in the public interest .... It is important that the digital planning platform to be provided as public infrastructure, governed in the public interest and using open technology, including:

- ***Machine readable digital content:*** *Ensure that content published and procured in public planning processes is easily processed by computers (machine readable), including the data and methods contained within them. Ideally, content is provided in accessible formats (i.e., XML and HTML) which are provided in addition to or instead of PDF files.*
- ***Standardization:*** *Standards should be developed for common language, processes and data in order to enable collaboration across jurisdictions.*
- ***Open data:*** *All non-sensitive data produced within public planning processes should be made available as open data, including development approvals data and 3D and 4D modelling publicly procured for digital twin development. Processes for the handling of sensitive data must be maintained.*
- ***Open rules:*** *Computer code representing planning rules used in automated or assisted public decision-making processes should be made publicly available.*
- ***Open-source code:*** *Where public funding is used in the development of new digital tools, these should be provided as open source to enable reuse across different agencies and authorities. Grants should be provided, and collaboration encouraged between different authorities so that no one agency disproportionately bears the cost of software development.*

These principles represent key changes required for planning practice to enable frictionless interactions, digital transparency, and cross-jurisdictional collaboration (PIA 2021).

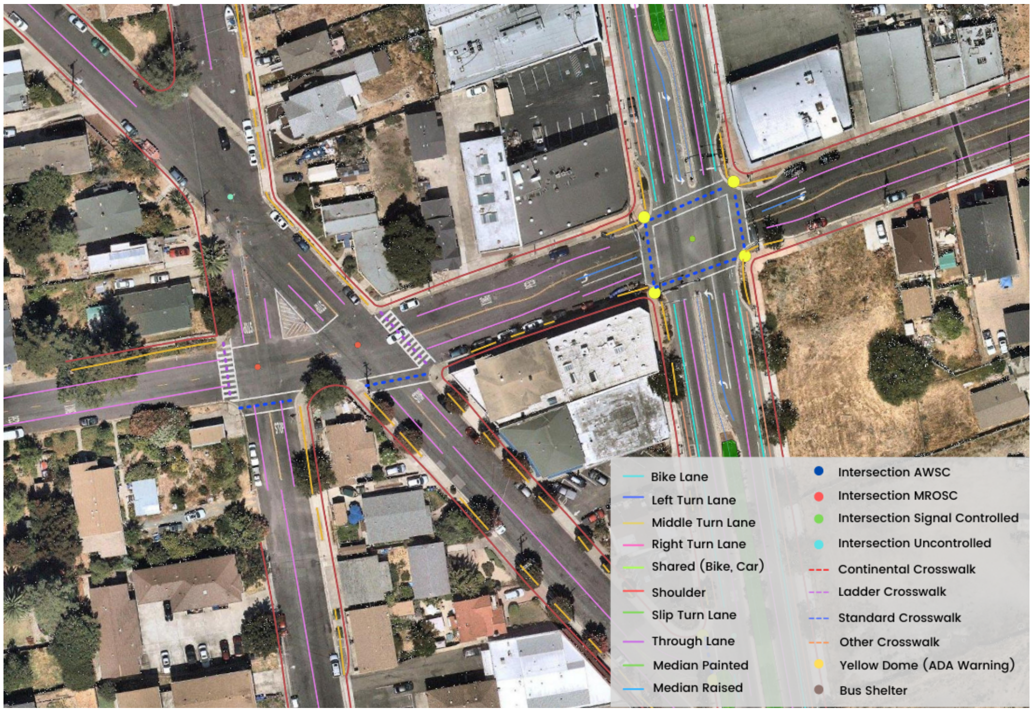


Figure 6. Contra Costa County's digitization of its rights-of-way (Ecopia)

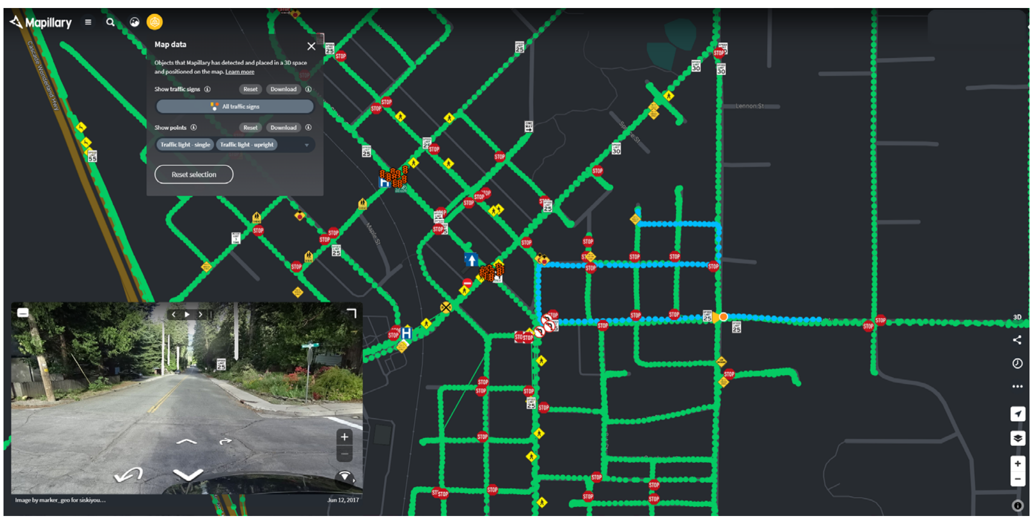


Figure 7. A sign inventory created for Mount Shasta, California, showing where AI detected stop signs (Meta Platforms, Inc.)

Beyond aerial imagery, street level images from Google Street View and [Mapillary]() are increasingly being used to digitize assets such as streetlights and stop signs that might be more difficult to reliably detect in aerial imagery. As part of a mobility plan, Alta Planning + Design used Mapillary to aid network screening and verifying a crosswalk inventory created by Ecopia in Mount Shasta, California (Figure 7).

Such scaled-up geolocated digital representations of the built environment can be used to create "digital twins" supporting informed decision-making, effective stakeholder engagement, and robust scenario-planning practices.

Urban Observation

Machine learning can now derive meaningful insights about how people interact with the built environment from standard street-level cameras. The resulting data can show real-time or aggregate metrics of impact before and after policy and design interventions, helping to determine their effectiveness.

The qualitative observations once carried out by the likes of Kevin Lynch and William Whyte can now be automatically captured and surfaced as data feeds. These feeds can address key problems for emerging areas of concern to planners, such as managing the growing and competing demands for curb space in cities (DeAngelis et al 2022).

As an example, curbside management analytics firm [Automotus]() provides curbside monitoring services based on computer vision-derived observations of curbside users like delivery drivers, pedestrians, taxis, transportation network companies, and other user groups (Figure 8, p. 7). Its technology

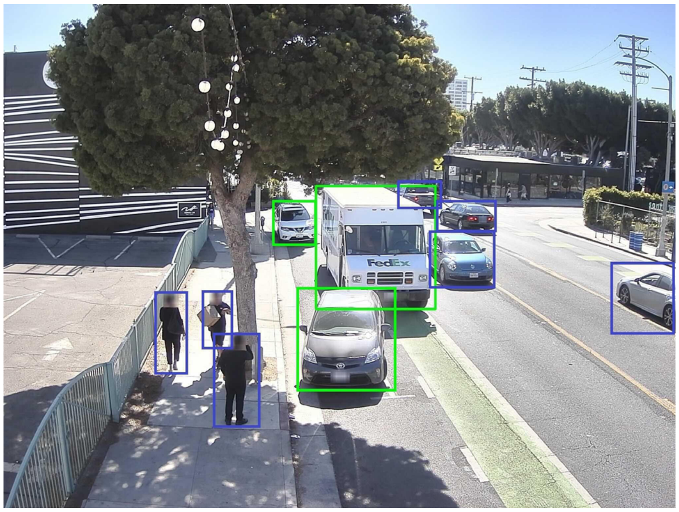


Figure 8. Computer vision can derive counts of delivery trucks, people, and other curbside users to better manage the curb (Automotus)

can provide real-time activity data and help with enforcement of new policies, such as piloting zero emissions delivery zones to help incentivize commercial adoption of electric vehicles (Automotus 2021).

This allows planners to empirically test the impacts of different physical or policy-based interventions in transportation, urban design, and other areas at a lower cost and more comprehensive scale than ever before. As more and more sensors are deployed in urban environments—in connected or autonomous vehicles, driver assistance systems, traffic cameras, and so on—the velocity and scope of new AI-derived insights for urban observation is likely to increase in the years ahead (Bayat and Kawelek 2021; Wasserman 2020).

Applications already seeing deployment include monitoring for parking occupancy, proactively evaluating safety, and multimodal counts (Wasserman 2020; Ding 2020). For example, Toronto's pedestrian projects team was challenged to measure the effectiveness of an upcoming curb modification. The city worked with software and services firm Transoft Solutions to transform the footage from temporary cameras to trajectories and incidents three days before and after the curb radius reduction, tracking conflict rates and the speed of turning vehicles involved in a conflict (Figure 9). The resulting data showed that the intervention decreased high-risk conflicts by 30 percent.

Digital Twins and Digital Futures

Smart city digital twins offer a digital replica of a city or region that takes in real-time data feeds and relays insights about the interactions between humans, infrastructure, and technology (Hurtado et al. 2021; Mohammadi and Taylor 2020; Adler 2016). These digital replicas can leverage advanced modeling to inform community narratives or illustrate scenarios to help the public understand the ripple effects of planning policy (Mohammadi and Taylor 2020). Just as the early applications of AI in urban planning were used to model future land-use change, smart city digital twins promise the ability to model a wider range of digital futures (Jain et al. 2011; Hurtado et al. 2021).

When planners make forecasts of the future to identify future local or regional community needs, using empirically valid and transparent methodologies is critical for stakeholder buy-in (Waddell 2011). Simulations model systems based on our understanding of the world to imitate their behavior and predict their effects (Adler 2016; Waddell 2011). For nearly a decade, the integrated land-use and transportation simulation model UrbanSim has been used by metropolitan planning organizations (MPOs) to build regional forecasts of potential land use, population, employment, and other changes based on projections and expected transportation investments (Figure 10, p. 8) (Waddell 2011).

Applications like UrbanSim exemplify the potential of interdisciplinary simulation models operating on digital replicas of

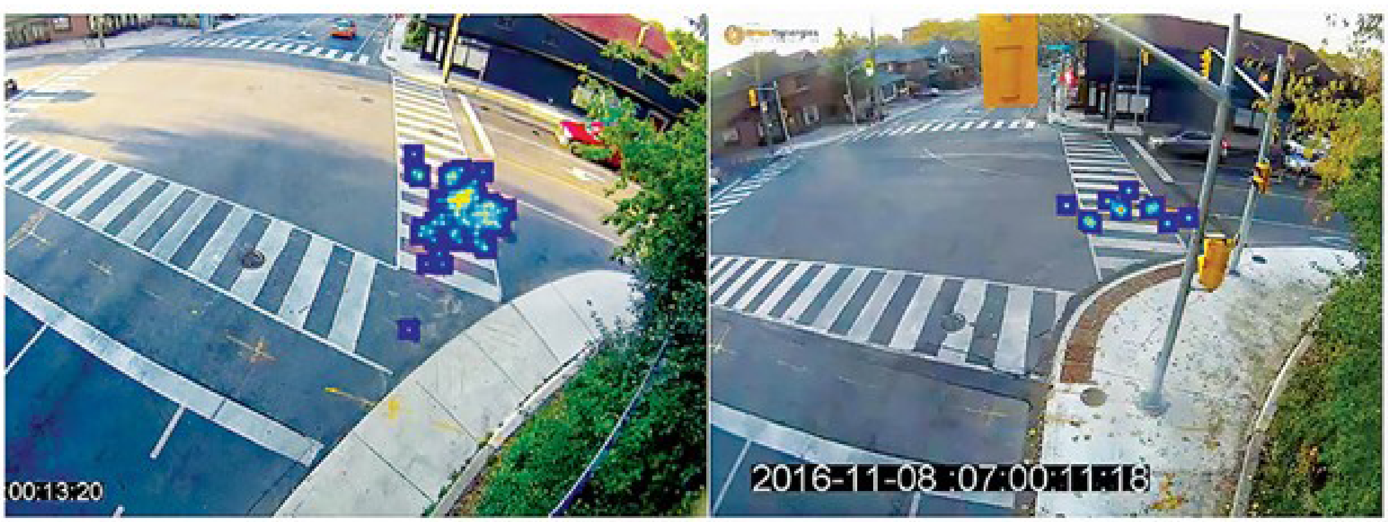


Figure 9. Temporary camera footage from Toronto shows conflict hotspots detected before curb radius reduction (left) and after curb radius reduction (right) (Transoft Solutions (ITS))

Figure 10. UrbanSim's UrbanCanvas web-based application aids with integrated land use and transportation modeling (UrbanSim)

land and infrastructure to identify possible futures for communities and regions.

Decision Support Systems

Decision support systems are information systems or interactive tools that help organizations make informed decisions about underspecified problems using frameworks that are flexible and adaptive (Snow 2021). In the future, decision tools may help with investment prioritization or help automate much of the tedious work in evaluating developments, zoning requests, or similar administrative procedures.

The use of checklists, complicated prioritization tools, or algorithmic decision tools to combat inconsistency and bias in policy decision-making is not unfamiliar to planners (Snow 2021; Wright 2019). Planning processes must not be "arbitrary and capricious" in either legal or political contexts (Snow 2021; Wright 2019). Having structured and fair processes to evaluate development proposals, their conformance to plans and codes, and their impact on the community is a regular part of development review or design evaluations (Zucker 2007). Recent publications have acknowledged the consistency and process benefits of algorithmic decision tools in zoning, such as scoring, and evaluation criteria used to evaluate development proposals and rezoning requests (Wright 2019).

For the development review process, AI-based tools could act as a type of inferential glue that connects digital submittals using Building Information Modeling (BIM), local GIS data, and evaluation criteria to more quickly evaluate development impacts, benefits, and conformance to local plans or permitting requirements (Figure 11). The automation and digital evaluation process could enable development review processes that are more nimble, responsive, and better integrated across departments and disciplines (Noardo et al 2022). Digital permitting systems such as [CivitPermit]are claiming to augment the permitting process by leveraging AI and GIS-BIM integration to facilitate more efficient and integrated evaluations (Soft Tech 2021; Noardo et al 2022).

Existing tools already used by planners might offer further capabilities for automated evaluation of metrics given a set of scenarios or designs. For example, [ArcGIS CityEngine] is known for providing planners a powerful set of procedural modeling techniques to quickly generate 3D models of blocks, buildings, and streets using rules that adjust based on data (number of floors, setback requirements) (Figure 12, p. 9) (Lechot 2020). For each set of models generated, metrics can be derived and then be used to "optimize" a zoning or design proposal based on the balance of benefits and costs (Lechot 2020). Such decision support tools that can iteratively evaluate scenarios can inform better planning and design and identify trade-offs early on in planning (Lechot 2020; Wright 2019).

Augmented Creativity

The importance of visual communications is not lost on planners, who use maps and 3D models to inform public narratives to guide policy decision-making. Creative applications of AI enable the generation of images and 3D content at incredible

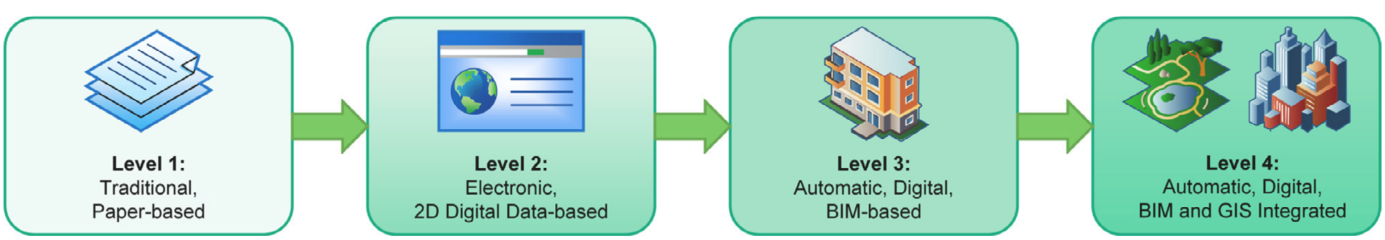


Figure 11. Regulatory and permitting processes have evolved from paper-based evaluations to digitally integrated BIM-GIS evaluation systems (Noardo et al. 2022)

Variables	Values range	Unit
Lot coverage	[0;100]	%
Tier height	]0;infini[	m
Building shape	{1,2,3,4}	-

Figure 12. Esri's ArcGIS CityEngine's procedural runtime can be used alongside optimization routines to identify different design scenarios given a set of zoning and design constraints (Camille Lechot, Esri R&D Center Zurich)

speeds (NVIDIA 2021; Nishida et al. 2016; Anderson 2021). This provides users with the ability to create increasingly complex visualizations and designs iteratively and efficiently.

NVIDIA Canvas is a prototype application that uses AI to transform rough sketches and blobs into photorealistic landscapes (Figure 13). In the future, image editors could create highly detailed landscape visualizations from simple blocks of color. As it stands, companies such as Adobe are increasingly integrating AI capabilities into their software so users can replace the sky of one image with another, change background lighting, or automatically select the subject of images (Adobe 2019). This could enable planners and urban designers to create more engaging visualizations faster and at lower cost.

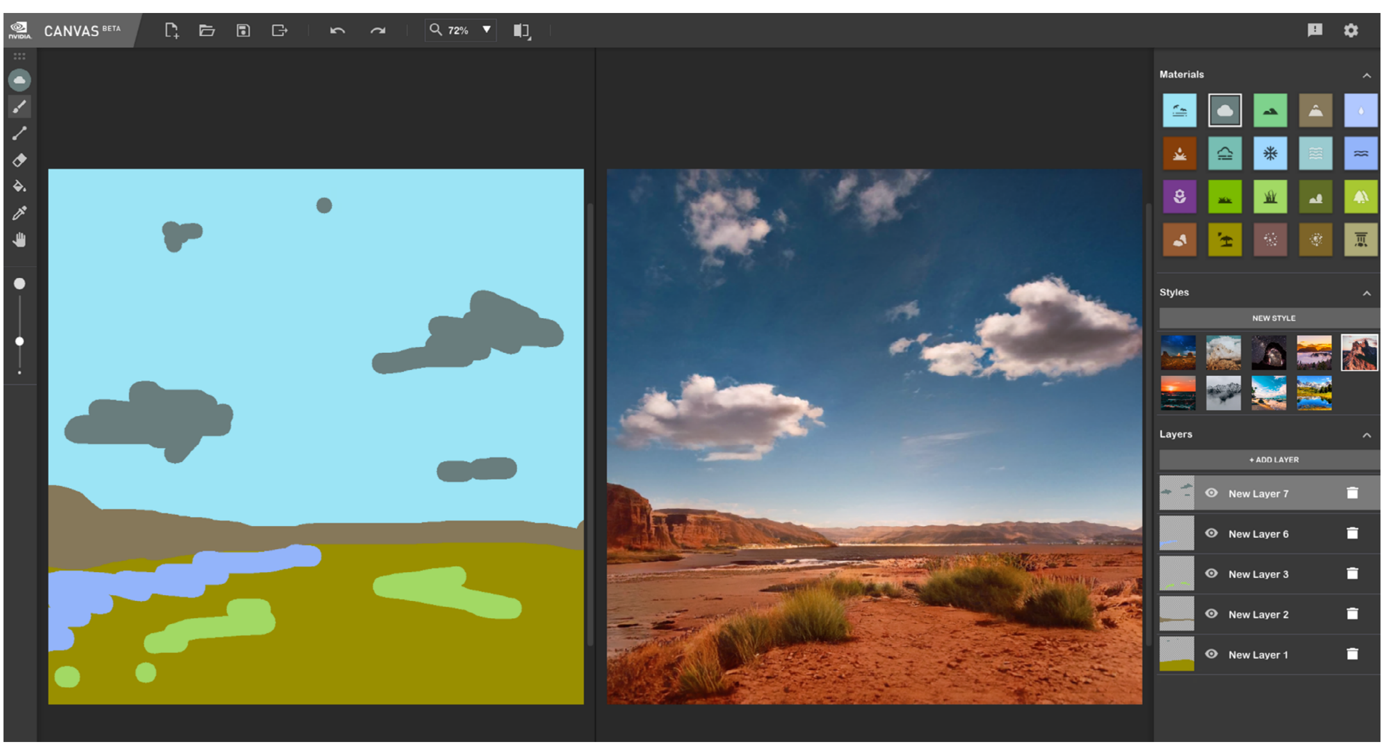


Figure 13. NVIDIA Canvas transforms rough sketches and blobs into photorealistic landscapes (NVIDIA)

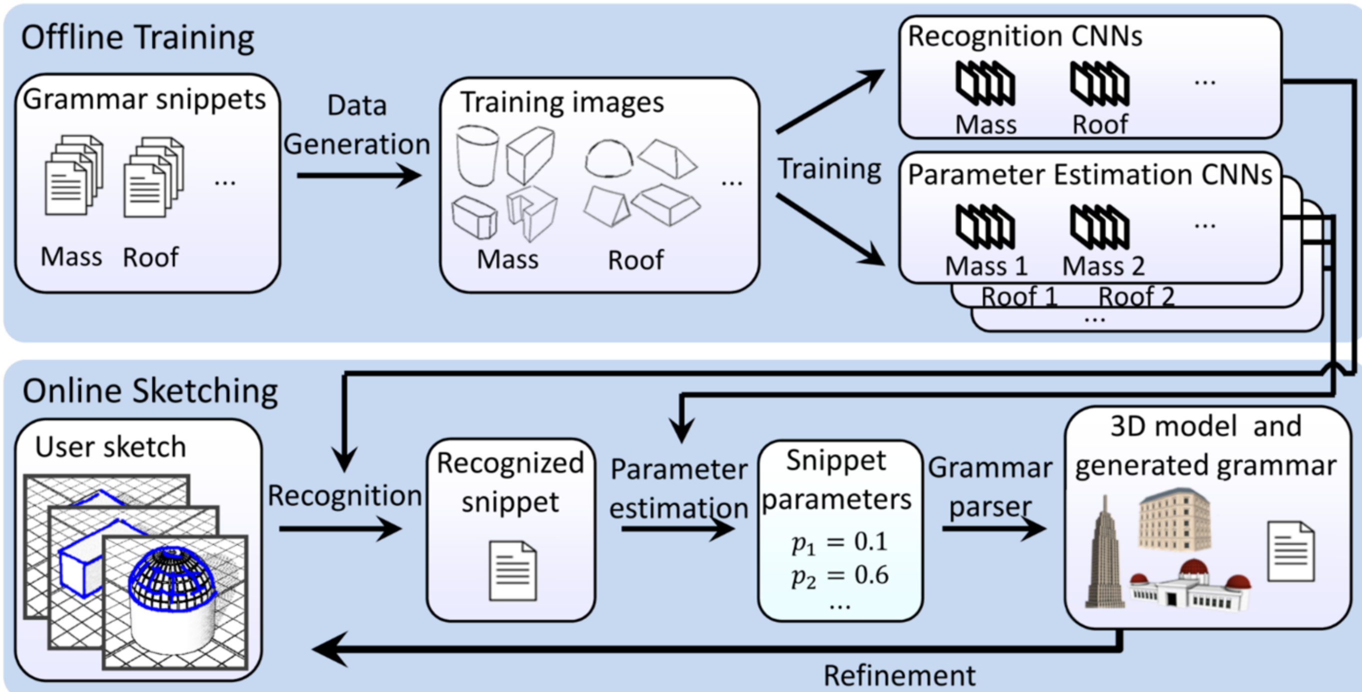


Figure 14. Researchers trained AI models to connect rough pencil-sketched images to shape grammars, transforming them into more complex and sophisticated 3D models (Nishida et al. 2016)

Similarly, machine learning-infused parametric design approaches are being developed within the worlds of architecture and urban design that enable more rapid prototyping of different design scenarios and space configurations (Anderson 2021). Researchers tested a framework in which AI models were trained to connect rough pencil-sketched images to shape grammars that transformed them into more complex and sophisticated 3D models (Figure 14) (Nishida et al. 2016). Future applications could quickly translate rough sketches into more complete 3D models for planning communication and urban design.

When combined with the simulation and visualization potential of modern game engines, these approaches could allow planners to go more quickly from a design scenario idea to a fully rendered and interactive vision for a plan or project.

Reading the Room

How governments facilitate public deliberations on decisions remains one of the most contested topics in municipal governance and beyond (Williamson et al. 2004; Arnstein 1969). Advancements in natural language processing (NLP) are enabling new methods "to read the room" when governments are getting feedback from the public (Eggers et al. 2019).

Planners' understanding of their communities' needs is informed by understanding the public's comments in public meetings, charettes, web-based engagement applications, participatory budgeting exercises, and other forms of deliberation (Williamson et al. 2004; Denker et al. 2021). Connecting with communities helps planners understand the pace of trust for public actions and provides opportunities to earn it at a time when it is historically low (Brenan 2021).

When COVID-19 forced many public engagement and deliberation activities online in early 2020, there were already a considerable number of tools to create digital public forums (Denker 2021; Fedorowicz 2020). But online engagement tools are increasingly leveraging advancements in NLP to quickly synthesize components of people's feedback, such as their sentiments towards projects, or identify similar areas of feedback (Figure 15, p. 11) (Denker 2021; Fedorowicz 2020; Eggers et al. 2019). This can help planners synthesize large amounts of unstructured public comments when more open-ended feedback is desired (Eggers et al. 2019).

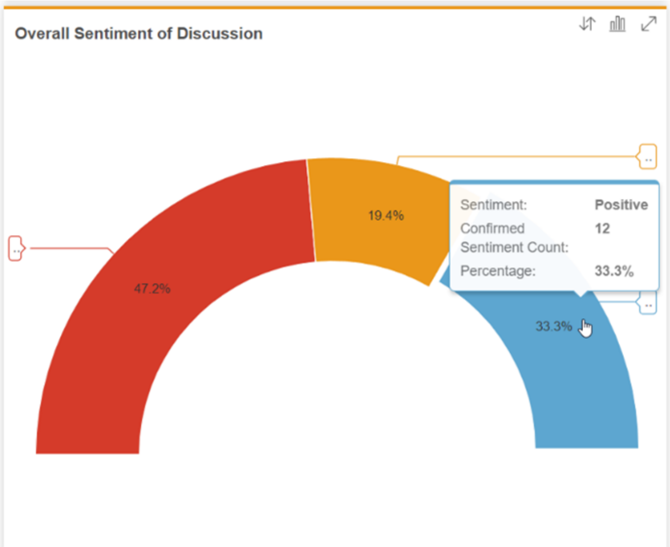
Considerations for AI and Planning

AI opens new possibilities for planning practice, but it requires awareness of the technological foundations underpinning planning methods and practice and acknowledgment of the risks associated with AI and related emerging technologies (OECD 2021a; Tomer 2019). Responsible and effective applications of AI in urban planning practice will depend on planners' understanding of these issues.

The following sections introduce planners to important considerations regarding the use of AI and the digitalization of planning practice. Readers are encouraged to consult the resources cited throughout these sections for more in-depth guidance on these topics.

Digital Skills Gaps

Both digital transformation and the informed application of AI technologies in planning practice will require new skills (Dimina 2019; Yigitcanlar 2020; Hurtado et al. 2021). Agencies such as



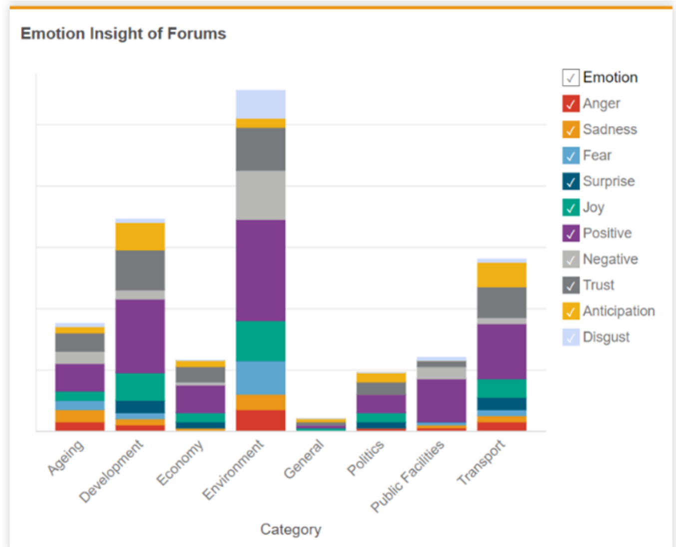


Figure 15. Public engagement platforms such as [Engagement HQ] can classify unstructured text from public comments into positive and negative sentiments and emotion classifications (Bang the Table)

the Los Angeles Department of Transportation (LADOT) have gone as far as to adopt the mantra, "Code is the new concrete," in recognition that digital infrastructure is increasingly becoming as important as physical analogs (LADOT 2020). LADOT's Technology Action Plan asserts that the development of a digital culture requires investment in personnel's skills and familiarity with key technologies.

While many planning practitioners are familiar with tools such as GIS, skills gaps in practice are emerging as modern technologies and civic analytics methods require new capacity in software expertise in technologies such as Python, R, JavaScript, SQL, and other tools (NACTO and IMLA 2019; Kontokosta 2018). Filling these skills gaps is critical to organizations' abilities to create value from the data they manage, ask the right questions of vendors during procurement, and communicate important touchpoints between technology and public process (NACTO and IMLA 2019; Kontokosta 2018). It is critical that planning professionals be informed consumers for the communities they serve (ITF 2019; Dimina 2019).

Explainability and Accountability in Public Policy

As noted above, when setting public policy, the decision-making process is just as important as the decision itself (Mayson 2018; Agontinelli 2021; Andrews 2019; Waddell 2011). But while machine-learning algorithms have demonstrated themselves to be quick and effective, often by their very nature they are not understandable or explainable—even by those who develop them.

For example, deep-neural networks and their relatives have known tradeoffs between their performance and the degree to which they can trace the basis of a prediction (Kontokosta 2018; Agostinelli 2021). This makes some of the most complex models very difficult to audit relative to simpler statistical models (i.e., linear regression). Thus, even if technology companies would allow planners to subject their software to external scrutiny, the degree to which any information could be derived from these "black-box algorithms" should be expected to be limited. This aspect of complex machine-learning algorithms makes them difficult to apply for major decisions in public policy contexts where explainable, verifiable, and accountable results are required (Barredo Arrieta et al. 2020; ITF 2019).

The planner's role in holding private companies accountable to the potential harms and risks associated with the deployment of AI-infused algorithms is more complex. The development of "explainable AI" (XAI) or methods to audit algorithms is an area of intense research and policy innovation (OECD 2021a; Barredo Arrieta et al. 2020).

The OECD AI Policy Observatory has compiled several publications that point to technical, procedural, and educational resources and tools that can be used to check for bias or robustness of AI systems and inform risk management guidelines (OECD n.d.). For example, given the centrality of data to the operation of machine-learning algorithms, some of the highlighted tools identify how to audit the underlying data used to train them (Gebru et al. 2021). Researchers in collaboration with Microsoft see a world where datasets come with datasheets that identify their operating characteristics, test results, recommended usage, composition, and other traits to increase transparency and accountability within the realm of machine learning (Gebru et al. 2021). The ability to audit algorithms and data is critical to any planner seeking to understand how to reduce the risks and harms applied AI could have on their communities.

Representation and Bias

Algorithmic bias and representation in machine-learning models have the potential to reinforce social disparities in communities when incorporated into business, administrative, and civic systems (Mayson 2018; Crawford 2021).

The composition and quality of training data used to build these models directly influence their performance (ITF 2019).

Machine-learning models learn patterns from data—thus, when the data is biased, so are they (Mayson 2018). Generally, this bias comes in two forms:

- *Biased training data:* a machine-learning model will inherit the underlying biases or historical discrimination embodied in training data (Gupta et al. 2021; ITF 2019)
- *Accuracy disparity*: A machine-learning model will perform more accurately on some groups relative to others. This can result from the composition of the training data having large asymmetries in how well distinct groups are represented in the dataset compared to others (ITF 2019; Yigitcanlar et al. 2020).

Both are connected to the underlying data used to generate predictive algorithms—but also to the blind spots of those constructing a predictive system. The act of classifying or counting something involves a preconceived notion of what is worth counting or classifying (Crawford 2021). Whether special attention is paid to how well vulnerable communities are represented in both data and in technology communities will influence who benefits from these technologies and who is left behind (Hurtado et al 2021).

A core concern for bias in algorithmic decisions is that it can enable institutional discrimination at massive scales (Mayson 2018). Even slight bias aggregated across a software system or planning tool could influence more decisions than any one individual. On the other hand, cognitive bias and irrationality in human judgement is held to a lower bar of accountability (Mayson 2018).

In theory, the operations and outputs of algorithms can be inspected to measure their bias, a task difficult to achieve for human decision-making in practice (Mayson 2018; OECD 2021a). Algorithmic risk assessments are clearly needed to understand the potential impacts of algorithms' integration into our civic institutions and planning systems (ITF 2019; Mayson 2018).

When Past Should Not Be Prologue

Planning requires thinking about how policies and public investments shape potential pathways for community futures (Wright 2019). Statistics and machine learning will develop predictive models for the future based on past data, and by so doing the insights created from them use the past as prologue (ITF 2019; Mayson 2018). There are two major concerns, however, regarding the application of these models:

- **Cementing past mistakes.** Basing decisions on predictions from historical data is likely to repeat and reinforce the outcomes of the past (Mayson 2018). This can often follow the use of metrics or data that are convenient or at hand, with outputs reinforcing historic values or creating unintended outcomes (Crawford 2021). Predictive models can mirror how we have historically addressed problems rather than reflecting the lens we bring to them now (Mayson 2018). In other words, we risk automating processes that were problematic to begin with because they will "inherit" the analytical frame of the system they originate from.
- **Managing change.** Predictions based solely on historical data will not adapt to changing conditions. For example, a planning challenge likely to define the 21st century will be planning for a changing climate. As of 2019, carbon dioxide concentrations not seen for two million years are clear examples of how pure machine-learning models may not provide as much value in an environment where conditions change (IPCC 2021).

For these reasons, care should be taken when these algorithms are applied in situations with high degrees of uncertainty or unprecedented circumstances, or where they are likely to reinforce undesirable historical outcomes.

Error Minimization Is Not Zero Error

A key aspect to understand about applications leveraging machine learning is that as statistical engines, they work through the minimization of measures of error in their predictions, often called loss (Google 2020; Ding 2020).

The errors that can occur in machine-learning systems have analogues to those from statistics, such as false positives and negatives, but some are more complex (Ding 2020). For example, technologists at Numina have documented many of the errors that can occur for computer vision-based street-level observation. These include *detection errors*, when an entity is misidentified in the image or in the wrong location; *classification errors*, when an identified entity is misclassified as another; and *tracking errors*, when an entity is correctly detected or classified, but a break in its path tracking occurs and inflates resulting entity counts (Ding 2020).

When planners consider the potential integration of machine learning into infrastructure or processes, its application should be judged from an understanding of consequences to individuals or the public if it is wrong (ITF 2020; Mayson 2018). For example, planners working on an AI-derived asset inventory project can set aside time for manual review if there are some paths incorrectly classified as sidewalks or company logos on vans misclassified as stop signs. However, integration with sensitive or critical infrastructure deserves more scrutiny. Real-world consequences can follow from prediction errors, with a poignant example being the role of classification error in an autonomous vehicle's motion planning that led to the tragic death of a pedestrian in Tempe, Arizona (NTSB 2018).

Data Protection and Privacy

Machine learning-based applications depend on data to function. How this data is collected, managed, and secured can have important policy implications about data protection and privacy (Andrews 2019; LADOT 2020).

Much of the recent history of machine-learning benchmarking datasets has been defined by a lack of consent of those captured to train new algorithms. For example, the DukeMTMC project for multitarget facial recognition was highly controversial because it collected over two million frames of 2,000 students walking between classes without their consent and

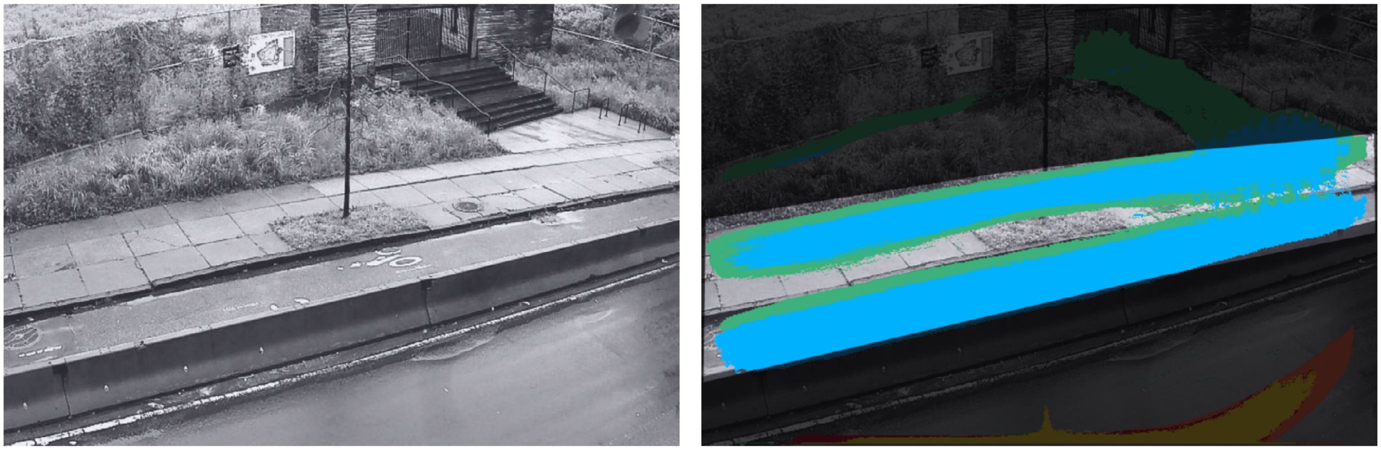


Figure 16. Numina's sensor technology uses edge computing to provide multimodal traces of bicyclists and pedestrians using a greenway in Brooklyn, New York (Numina)

was subsequently leveraged in surveillance software (Crawford 2021). While this dataset was removed from the internet because of the furor it caused, it is an important reminder that for planning purposes, data should only be collected to achieve specific purposes and privacy should be protected to the greatest extent possible (LADOT 2020).

Certain data collection technologies, such as video capture and GPS traces, can collect personally identifiable information (PII) about the subjects they observe, which has data security and privacy implications (NACTO and IMLA 2019). Any transmitted data could theoretically be intercepted by an unauthorized third party (ITF 2019; LADOT 2020; NACTO and IMLA 2019). Security concerns can pose liability risks to planning departments and related public-sector organizations leveraging these technologies.

One way to mitigate these risks is with a "privacy by design" approach that protects the individuals observed from the onset of the data collection process, typically by collecting and keeping as little data as possible to get the job done (NACTO and IMLA 2019; LADOT 2020; Tomer 2019). Related strategies include:

Figure 17. Anonymization techniques include the use of automated processes to blur faces detected in street view images (Meta Platforms, Inc.)

- **Edge computing.** Instead of transmitting live sensor readings or images to a server to be processed, images or other sensor data can be pre-processed on the device and transmitted in an anonymized form (such as pedestrian or bicyclist traces or counts). This reduces the risk of any interception of sensitive data and protects privacy of those scrutinized by design. For example, traffic data collection company Numina's sensor technology uses edge computing to process the footage it collects so that only AI-derived traces of user behavior are sent over the internet (Figure 16). This means even if data is intercepted, the privacy of those observed is respected by design.
- **Anonymization techniques.** Another approach that might be less secure but still protects privacy is to anonymize images collected by blurring faces and similar data characteristics (Figure 17). This approach may still be vulnerable to data interception or similar risks, but it can ensure when data is used that verified efforts are made to protect the identity of those observed. All image data collection efforts should employ at least this level of privacy protection.

Data Ownership and Licensing

In many cases, firms providing AI-derived data or services treat their data and related products as a competitive advantage. This view of their products can limit transparency into how the data is derived and may limit how planners can use the data.

For example, data vendors and civic technology firms commonly provide licenses that allow use of the data without providing complete ownership, similar to software licenses. Often these data licenses will restrict how the data is used to prevent data sharing or even comparison to similar outputs from other firms. This can have significant implications with what role licensed data can play in open data ecosystems in which this data is provided to the public to increase accountability, transparency, and integration (Bayat and Kawalek 2021). The terms and conditions that apply to procurement data and technology services can have important implications, such as increasing the complexity of agencies' data management operations, reducing market competition for civic solutions, and limiting the transparency of data informing public decisions.

Action Steps for Planners

Planners should consider the following recommendations to leverage AI responsibly in a planning context. This list is by no means comprehensive, but it should provide a starting point for those wishing to support and integrate AI applications into their processes.

Take a needs-first approach to solution selection. To effectively apply AI, planning practitioners should start by identifying community or organizational needs that advancing AI capabilities can help meet.

There can often be a barrage of advertising to planners for smart city or AI applications that can be classified as solutions in search of problems. The most effective applications of these technologies are often developed in response to extant planning problems and needs. For example, many of the practice-focused applications discussed in this *Memo* center on how advancements in AI can change how we collect data. Internal discussions can be facilitated that center on questions such as:

- What gaps currently exist in our community's data systems?
- Does our community already have a digitized sidewalk, crosswalk, or tree inventory?
- Do our property appraisers have automated methods to identify changes to properties based on aerial imagery?
- How have we previously evaluated changes in performance of changes in street design?

Develop a technology action plan. Organizations fall along a wide spectrum of experience regarding data transparency and management as well as deployment of advanced technologies. A technology action plan, such as the [LADOT Technology Action Plan] referenced earlier in this article, can help identify opportunities for municipal and regional governments to identify data sharing and digital services that can advance better cross-departmental collaboration and problem solving.

Key components of technology action plans include guiding principles and values and a review of the skills and infrastructure investments required to address identified needs. An internal plan should explicitly state how issues related to investments of IT infrastructure, upskilling staff, representation, privacy, roles of different departments, and data ownership will be managed; specify an outreach plan; and identify near-term pilot projects to move planning into action.

Support and promote digital literacy. It is critical to upskill staff to be digitally literate. Planners must understand how the digital spheres of our lives impact the public interest to base decisions on them (DeAngelis et al. 2022).

As organizations adopt civic technologies, there is an increasing need for planners who can apply them to civic problems. Organizations can foster digital literacy in a number of ways:

- Support continuing education of staff regarding becoming familiar with emerging technologies.
- Listen to, promote, and recognize action-oriented planners willing to work between the digital, physical, and governance spheres of planning.
- Review emerging legal, policy, and regulatory resources, such as those provided by the OECD AI Policy Observatory or Oregon State University's Nexus.
- Conduct digital needs assessments and become familiar with important digital services best practices from resources such as OECD's Digital Government Toolkit, E-Leaders Handbook on Digital Government, and Digital.gov.
- Familiarize staff with key civic technology aggregators such as the civic technology field guide or the APA Technology Division's urban and regional planning resource page. These pages link to rich collections of different technology service providers, tools, data, and vendors.

Support experimentation. Innovation requires nurturing systems that encourage it. Planners should help their organizations identify and eliminate barriers to entry for procurement contracts.

Conventional procurement processes can demand extensive experience requirements or a high degree of specification regarding how tasks are done that bias procurement toward incumbents who provide tried-and-tested solutions (Ortmans 2015). Constructing scopes of work and vendor requirements for projects and programs that don't exclude start-ups and creative approaches is an important step towards supporting more public-sector innovation. Consider pilot projects, internal team trainings, technology exchanges, university partnerships, coordinating with programs supporting young companies, and "entrepreneur-in-residence" programs.

Plan for real-time expectations. The transportation sector is already seeing a revolution in expectations regarding how systems are expected to adapt to changing needs almost instantaneously. The pace of processing and the expectation of quickly informed decision-making is taking place across the economy, and its influence on the expectations of civic processes including planning, zoning, and permitting will likely be hard to ignore. These expectations are quite acute when we consider how planning systems need to respond to post-disaster crises in a world undergoing climatic shifts (IPCC 2021).

Planners need to balance the careful long-term thinking required for comprehensive planning activities with the changing expectations of developers and the public for accessible and agile "front end" planning processes.

Consider the reversibility principle. The reversibility principle holds that when we consider deploying a new technology, we prioritize the application of products and processes whose negative impacts will cease when withdrawn.

As with other new technologies, to maintain urban resilience, initial applications of AI should be made in investments whose impacts are reversible. Initial deployments of AI technology for civic purposes thus should be guided by the ability to back out of agreements, manage risks, and ultimately cease the application of these technologies if negative impacts are outsized relative to benefits. This might mean working with subscriptions through vendors that are easier to cancel and avoiding deep integrations into mission-critical systems, such as emergency services.

Develop and support machine-readable regulations and codes. Planners should actively work to develop open and machine-readable regulations and codes to prevent misalignment between third-party interpreters and the actual law. This means finding ways to digitally distribute the rules behind policies—ideally, using accessible text formats such as HTML, XML, and Markdown alongside or instead of PDFs.

The ability of the planning profession to maximize the benefits of civic AI will depend on our ability to develop consensus-based standards defining the digital representation of zoning codes, curbside regulations, street layouts, bike facilities, easements, and other legal constructs. Planners should actively seek to increase their awareness of relevant data standards and support their adoption if those standards can support planning in their communities.

Adopt data standards and consider interoperability and system integration. One of the benefits of AI-derived data is that it provides a repeatable, scalable, and standardizable approach to collecting data of a potentially arbitrary definition. However, much of this benefit will be lost if planners do not proactively define what is needed to solve planning problems and standardize it.

If every region reinvents the wheel when developing solutions, the shared value created by emerging AI algorithms will be slow to realize. Sharing standards and templates for quality assurance approaches could go a long way towards ensuring that planners have baseline methods to assess AI-derived data.

Similarly, for communities and planning processes to see tangible benefits from most advances in software and technology, solutions need to provide integrated workflows across multiple stages of the planning process and encourage collaboration across departments. This challenge is particularly salient when considering the need for solutions to address problems across different spatial and temporal resolutions and between disciplines.

Prioritize ethics, equity, and privacy protection in implementing AI. Special attention should be given to applications related to understanding how AI systems will influence outcomes for vulnerability community members as part of planning processes. This consideration extends to how AI systems are developed and deployed within public and private systems within our communities.

For civic applications of AI to be politically acceptable, planners should directly address the public about privacy. All stored data derived from AI systems should actively have PII stripped from it.

Consider bias and representation. Planners have a role in working to establish fair civic processes and apply AI responsibly, if at all. This will mean paying careful attention to whether open-source solutions provide documentation on the steps they followed to have well-represented training datasets. When working with technology providers, planners can ask whether their models were trained on datasets that were developed with inclusive representation in mind.

Understanding who an algorithm leaves behind means identifying methods to audit algorithms and asking questions about the curation process and composition of training data. Planners should support calls for greater transparency in the development processes of machine-learning datasets through the creation of datasheets that identify important questions that help inform planner's assessments of the potential for algorithmic bias (Gebru et al. 2021).

Actively develop training data. Data comes in many forms and contexts, including audio and imagery sources—not just conventional tabular or GIS data. Planners can help define what should be digitized, what should be made public, and what should be protected. They should prioritize the use of data collection processes that protect privacy, are resource efficient, and avoid exploitative crowdsourcing systems. Remember that machine-learning algorithms require much larger training set sizes than conventional statistical techniques, and so either automated data acquisition or partnerships with neighboring or similar communities may be required to get to useful sample sizes.

A promising area for exploration is the development of planning-specific synthetic datasets comprised of data from renders of virtual worlds or generative algorithms (Andrews 2021). For example, a 3D model of street-oriented buildings and buildings set back from their frontage could have renders taken from multiple angles to train a computer vision algorithm to identify the differences between them, irrespective of perspective. Datasets such as Cityscapes and Synthia are examples of rendered datasets that suggest how data for cities can be designed to support planning-specific problems (Andrews 2021; Nikolenko 2019).

Conclusion

A world governed by algorithms has immense promise and peril. Machine learning has the potential to create insights and inform decisions in a world awash with data, changing planning practice across multiple specializations.

As AI-infused technologies interweave into practice, planners will need to retain their focus on how to facilitate desirable long-term community outcomes and their willingness to tackle the complexity so entangled with the wicked problems that planning endeavors every day to confront. The key breakthroughs in AI can help communities digitize their infrastructure or land use, reinvent urban observation, forecast alternative community futures, inform decision-making, accelerate design processes, and help read the room during public engagement and public deliberations.

On one side, we can envision digital twins that help with projecting the intended or unintended consequences of interventions or policies so we can chart informed pathways for better community outcomes. On the other, naive application of these technologies can pose risks to community resilience, reinforce existing inequities, yield poor returns, and erode community trust.

These divergent views of AI's role in future decision-making are a reminder that the act of prediction is a mirror. Its reflection is more than a single inductive inference—it is an image of our collective past and values. If we do not like what we see, it can be interpreted as a judgment of ourselves as well as the technology's application. Planners' roles in civic decision-making give them some influence and agency of what this collective image looks like, and it starts by bringing a critical lens to questions about the data, values, and motivations enveloping what we collectively understand as AI.

About the Authors

David Wasserman, AICP, is the data science practice leader at Alta Planning + Design. His work lies at the intersection of urban informatics, 3D visualization, geospatial analytics, and visual storytelling. His current areas of focus are enabling data-informed scenario planning, incorporating civic data science into planning projects with web delivery and computer vision-derived datasets, and generating accessibility metrics that can identify the possible benefits of projects and who they go to.

Michael Flaxman, PHD, is the spatial data science practice lead at Heavy.ai. After 20 years of working within the domain of spatial environmental planning, he now actively works to develop the next generation of geospatial computing technologies at Heavy.ai. His main goal is to continue to develop spatial scenario planning tools, ultimately to bring the benefits of sustainable environmental planning to a much wider global audience.

References and Resources

Adler, Laura. 2016. "SimCities: Designing Smart Cities Through Data-Driven Simulation." *Data-Smart City Solutions*, August 29.

Adobe. 2019. "Amplifying Human Creativity With Artificial Intelligence." *Adobe Basics*, April 4.

Agostinelli, Forest. 2021. "Why It's Vital that AI Is Able to Explain the Decisions It Makes." *World Economic Forum Industry Agenda*, January 20.

American Forests. 2021. Tree Equity Score.

Anderson, Martin. 2021. "AI in Architecture: Is It a Good Match?" *IFlexion Blog*, January 18.

Andrews, Gerard. 2021. "What Is Synthetic Data?" *The NVIDIA Blog*, June 8.

Andrews, Leighton. 2018. "Public Administration, Public Leadership and the Construction of Public Value in the Age of the Algorithm and 'Big Data.'" *Public Administration 97(2): 296–310.*

Arnstein, Sherry R. 1969. "A Ladder of Citizen Participation." *Journal of the American Institute of Planners* 35(4):216–24.

Automotus. 2021. Computer Vision Based Curbside Management Technology.

Bang the Table. 2021. EngagementHQ Platform.

Barredo Arrieta, Alejandro, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, et al. 2020. "Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges Toward Responsible AI." *Information Fusion* 58(June): 82–115.

Bayat, Ali, and Peter Kawalek. 2021. "Digitization and Urban Governance: The City as a Reflection of Its Data Infrastructure." *International Review of Administrative Sciences*.

Brenan, Megan. 2021. "Americans' Trust in Government Remains Low." *Gallup News*, September 30.

Council of Europe. 2020. History of Artificial Intelligence.

Crawford, Kate. 2021. *Atlas of AI*. Yale University Press.

DeAngelis, Joseph, Alexandra Gomez, Petra Hurtado, and Sagar Shah. 2022. *Digitalization and Implications for Planning*. American Planning Association and Lincoln Institute of Land Policy.

Denker, Marisa, Mike Flynn, Samantha Donovan, Theresa Carr, and Alexandra Zazula. 2021. "It's Time for Public Participation To Evolve With Transportation Planning." *Planetizen, November 15.*

Dimina, Frank. 2019. "How Local Governments Can Harness AI." *American City & County*, August 12.

Ding, Jennifer. 2019. "Brooklyn Greenway Case Study: Pedestrian and Bicycle Activity in Public Spaces." *Numina Blog*. January 3.

———. 2020. "Defining Accuracy for Street Level Mobility Data." *Numina Blog*, February 27.

Ecopia AI. 2021. "Contra Costa County Public Works Partners With ECOPIA AI to Create Right-of-Way Transportation Planning Maps." *Ecopia AI Blog*, October 29.

Eggers, William D., Neha Malik, and Matt Gracie. 2019. *Using AI to Unleash the Power of Unstructured Government Data*. Deloitte Center for Government Insights.

Fedorowicz, Martha, Olivia Arena, and Kimberly Burrowes. 2020. *Community Engagement During the COVID-19 Pandemic and Beyond*. Urban Institute. September.

Gebru, Timnit, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé III, and Kate Crawford. 2021. "Datasheets for Datasets." *arXiv.org*, December 1.

Google. 2020. *Introduction to Machine Learning*. Google Developers, online course.

Gupta, Abhishek, Marianna Ganapini, Renjie Butalid, Muriam Fancy, Alexandrine Royer, Ryan Khurana, et al. 2021. *The State of AI Ethics Report*. Montreal AI Ethics Institute.

Hurtado, Petra, with Benjamin G. Hitchings and David C. Rouse. 2021. Smart Cities: Integrating Technology, Community, and Nature. PAS Report 599. Chicago: American Planning Association.

Intergovernmental Panel on Climate Change (IPCC). 2021. "Summary for Policymakers." In *Climate Change 2021: The Physical Science Basis*: *Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Valérie Masson-Delmotte, Panmao Zhai, Anna Pirani, Sarah L. Connors, Clotilde Péan, Yang Chen, Leah Goldfarb, et al. Cambridge University Press.

International Transport Forum (ITF). 2019. *Governing Transport in the Algorithmic Age*. Corporate Partnership Board Report.

Jain, Kamal, and Payal. 2011. "A Review Study on Urban Planning & Artificial Intelligence." *International Journal of Soft Computing & Engineering* 1(5): 101–4.

Klosterman, Richard. 1999. "New Perspectives on Planning Support Systems." *Environment and Planning B: Planning and Design* 26: 317–20.

Kontokosta, Constantine E. 2018. "Urban Informatics in the Science and Practice of Planning." *Journal of Planning Education and Research* 41(4): 382–95.

Lechot, Camille. 2020. "Generating 3D Content in Python: PyPRT, a New Python Library." Esri Blog, February 2.

Los Angeles Department of Transportation (LADOT). 2020. *Technology Action Plan*.

Mapillary. 2021. Mount Shasta AI Extractions.

Mayson, Sandra G. 2019. "Bias In, Bias Out." 128 *Yale Law Journal* 2218 (2019), University of Georgia School of Law Legal Studies Research Paper No. 2018-35.

McCarthy, John. 2012. What is AI?/Basic Questions. Stanford University.

McHugh, Bibiana. 2013. "Pioneering Open Data Standards: The GTFS Story." Chapter 10 in *Beyond Transparency*, edited by Brett Goldstein with Lauren Dyson. Code for America.

Miller, Ben. 2021. "Government Chatbots Now a Necessity for States, Cities, Counties." *Government Technology*, January/February.

Mohammadi, Neda, and John Taylor. 2020. "Smart City Digital Twins." *PAS QuickNotes* 89. Chicago: American Planning Association.

National Association of City Transportation Officials (NACTO) and International Municipal Lawyers Association (IMLA). 2019. *NACTO Policy 2019: Managing Mobility Data*.

National Transportation Safety Board (NTSB). 2018. *Collision Between Vehicle Controlled by Developmental Automated Driving System and Pedestrian, Tempe, Arizona, March 18, 2018*. Accident Report NTSB/HAR-19/03.

Neuhold, Gerhard. 2018. "Accurate Privacy Blurring at Scale." *Mapillary Blog*, April 19.

Nikolenko, Sergey I. 2019. "Synthetic Data for Deep Learning." *arXiv.org*, September 25.

Nishida, Gen, Ignacio Garcia-Dorado, Daniel G. Aliaga, Bedrich Benes, and Adrien Bousseau. 2016. "Interactive Sketching of Urban Procedural Models." *ACM Transactions on Graphics* (SIGGRAPH Conference Proceedings 2016).

Noardo, Francesca, Dogus Guler, Judith Fauth, Giada Malacarne, Silvia Mastrolembo Ventura, Miguel Azenha, et al. 2022. "Unveiling the Actual Progress of Digital Building Permit: Getting Awareness Through a Critical State of the Art Review." *Building and Environment* 213(April): 108854.

NVIDIA. 2021. NVIDIA Canvas.

Organisation for Economic Co-operation and Development (OECD). n.d. OECD AI Policy Observatory.

———. 2019. *The Path to Becoming a Data-Driven Public Sector*. OECD Digital Government Studies.

———. 2021. *The E-Leaders Handbook on the Governance of Digital Government*. OECD Digital Government Studies.

———. 2021a. *Tools for Trustworthy AI: A Framework to Compare Implementation Tools for Trustworthy AI Systems.* OECD Digital Economy Papers.

Ortmans, Jonathan. 2015. "Challenging a Risk-Averse Government Procurement Culture." *Kauffman Foundation Currents*, October 5.

Planning Institute of Australia (PIA). 2021. PIA PlanTech Principles.

Reid, Elizabeth. 2020. "A Look Back at 15 Years of Mapping the World." *Google Keyword*, February 26.

Riggs, William, Chris Steins, and Shivani G. Shukla. 2019. "City

Planning Technology, 2019 Benchmarking Study." *Planetizen*, February 11.

Singh, Rohit. 2019. "Where Deep Learning Meets GIS." *Esri Arcwatch*, June.

Snow, Thea. 2021. "From Satisficing to Artificing: The Evolution of Administrative Decision-Making in the Age of the Algorithm." *Data & Policy* 2021(3): e3.

Soft Tech. 2021. What Is CivitPERMIT?

Transoft Solutions (ITS) Inc. 2022. Traffic Safety & Its Solutions.

Tomer, Adie. 2019. "Artificial Intelligence in America's Digital City." Brookings Institution.

UrbanSim. 2021. UrbanCanvas Modeler.

Waddell, Paul. 2011. "Integrated Land Use and Transportation Planning and Modelling: Addressing Challenges in Research and Practice." *Transport Reviews* 31(2): 209–29.

Wasserman, David. 2020. "The Art of Learning by Example." *Planning*, October.

Williamson, Abby, and Archon Fung. 2004. "Public Deliberation: Where Are We and Where Can We Go?" *National Civic Review*, Winter.

Wright, Norman. 2019. "Applying Algorithms to Land-Use Decision Making." *Zoning Practice*, March.

Yigitcanlar, Tan, Kevin C. Desouza, Luke Butler, and Farnoosh Roozkhosh. 2020. "Contributions and Risks of Artificial Intelligence (AI) in Building Smarter Cities: Insights from a Systematic Review of the Literature." *Energies* 13(6): 1473.

Zucker, Paul C. 2007. *The ABZs of Planning Management*. Second edition. West Coast Publishers.

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