Artificial Intelligence in Landscape Architecture: A Literature Review

1 Abstract

The use of artificial intelligence (AI) is becoming more common in landscape architecture. New methods and applications are proliferating yearly and are being touted as viable tools for research and practice. While researchers have conducted assessments of the state of AI-driven research and practice in allied disciplines, there is a knowledge gap for the same in landscape architecture. This literature review begins to fill the gap by searching and evaluating studies specifically focused on AI and disciplinary umbrella terms (landscape architecture, landscape planning, and landscape design). It includes searches of academic databases and industry publications that combine these umbrella terms with the main subfields of artificial intelligence as a discipline (machine learning, knowledge-based systems, computer vision, robotics, natural language processing, optimization). Initial searches returned over 600 articles, which were then filtered for relevance, resulting in about one hundred articles that were reviewed in depth. The work highlights trends in dissemination, synthesizes emergent AI-Landscape (AI-LA) themes, and argues for unifying dissemination and compilation in research and practice so as not to lose relevant AI-LA knowledge and be caught off guard in the built environment profession's next technological leap.

2 Keywords

landscape architecture, landscape design, landscape planning, machine learning, optimization, computational design

1 Introduction

Leaders in landscape architecture have declared the need to consolidate data and expertise from disciplines such as engineering, land planning, agriculture, and ecological sciences to give “artistic physical form to modern ideals of equity, sustainability, resilience, and democracy” (*ASLA Is Committed to Climate Action*, n.d.; *New Landscape Declaration*, 2016). Such an assertion is fitting since landscape architects see their profession as an intersection among all others dealing with spatial issues (Kullmann, 2016). As designers of all types of exterior spaces, landscape architects’ work involves near-constant coordination with experts in allied fields. This is especially evident in the current state of practice, where projects are increasingly scaling up in scope to meet open-ended, territorial scale challenges (Bryant, 2021; Polk, 2015). Yet, for all the diverse ways designers engage across disciplines, most simply lack the time, knowledge, or background to account for the sheer number of ‘design problem’ permutations arising from multifaceted issues such as climate change resilience, large-scale ecological degradation, and social equity. To this end, there is an emerging discussion around the potential of artificial intelligence (AI) to address such limitations. The discussion includes topics like laying a historical groundwork for AI (Z. Zhang, 2020), current and potential AI applications to landscape architecture (Cantrell et al., 2021), proposing machine learning primers and ontologies (Alina et al., 2016; Fernberg et al., 2021; Tebyanian, 2020), gauging the potential for AI in coastal adaptation (Z. Zhang & Bowes, 2019), and conceptualizing an autonomous post-human ecological infrastructure (Cantrell, Martin, et al., 2017).

Still, AI-focused literature remains underdeveloped in landscape architecture, leaving knowledge seekers to turn to adjacent disciplines where the research is less nascent. The majority of current research in AI systems for landscape design or planning focuses on either conceptual exercises or somewhat singular tools for specific applications. Even if current explorations evoke broad observations about AI in landscape, a lack of compilation presents key unanswered questions:

1) What exactly do we mean when we say AI in the context of landscape architecture?
2) How has AI been used in landscape architecture research/practice, if at all? And
3) Where are our current knowledge gaps with regard to AI?

This literature review seeks to lay a foundation to begin answering these questions. In it, we: 1) establish a scope of review for landscape architecture and its subfields, 2) identify a framework for artificial intelligence as a research area within which to embed the landscape disciplines (i.e. the definition of AI as a discipline along with its sub-fields), 3) combine those terms to perform a literature search using online databases, and 4) after refining results, we provide a summary of trends, highlight emergent themes, and present the need for a future AI-Landscape (AI-LA) research framework.

2 Defining Review Parameters

2.1 "Terms" of Landscape Architecture

Landscape architecture practice is interdisciplinary, so it can often be difficult to delineate what falls under its purview. Grading, for instance, is a design exercise that can reasonably be claimed by both engineers and landscape architects but is often taught, talked about, and executed quite differently by each discipline. The same holds for many activities landscape architects carry out (e.g. stormwater management, construction documentation, landscape history, etc.). We recognize defining the scope of practice within landscape architecture is integral for a comprehensive and systematic review of AI's pervasion into the entire discipline—and that such an undertaking could be enhanced by using established frameworks such as the Landscape Architecture Body of Knowledge (LABOK) survey findings (2004) or Langley et al.'s knowledge domains of landscape architecture (2018). However, the combination of these multi-level conceptual frameworks with the scope of artificial intelligence is extremely vast. There have indeed been efforts to frame the context of the AI-LA knowledge base (Cantrell et al., 2021; Tebyanian, 2020; Z. Zhang, 2020), but these works did not intend to comprehensively review and formalize an AI-LA framework. Thus, for this review, we first needed to establish a simple but encompassing disciplinary scope as the foundation for this framework. We chose to adopt Ogrin's definition of landscape architecture as a discipline which comprises design and planning as two distinct subfields of creative work (1994). Hence our scope uses the three disciplinary terms from Ogrin: landscape architecture, landscape design, and landscape planning. These are often used interchangeably, and though sometimes seen as distinct in detailed discussions of practice, they can confidently be lumped into a representative set that represents the same discipline for the purposes of this review (von Haaren et al., 2014).

2.2 Artificial Intelligence and Applicable Subfields

The *Oxford English Dictionary* defines the term artificial intelligence (or AI) as "the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages." In the context of the AEC industry, the is often used colloquially as a catch-all for highly technical or computational approaches toward design and automation. The term machine learning is also used in common speak, often interchangeably with AI, even though it technically represents only a subset of the AI field. The scope of AI is extremely vast, which has led to the derivation of several subfields or branches. Here we outline some of the more common subfields seen in literature to provide a framework for how we conceptualize the contributions and application of AI within landscape architecture. The primary subfields we explore in this paper include: 1) *Machine Learning*, 2) *Knowledge-based Systems*, 3) *Computer Vision*, 4) *Robotics*, 5) *Natural Language Processing and 6) Optimization* (Abioye et al., 2021; Public Health Agency Canada, 2020). We acknowledge there is a range of other proposed subfields (Chiabai et al., 2018; Mata et al., 2018; Zhu & Yan, 2015), but for this review we chose these six as they are the most applicable to landscape architecture.

Machine learning. Machine Learning is one branch of AI, but the techniques often underpin a range of different subfields. The term itself may often be used as a synonym for artificial intelligence, perhaps because it is not well understood by non-experts or the diversity of AI subfields is not well understood (and ever changing). In simple terms, machine learning focuses on using statistical methods and models that can redefine and refine themselves to “learn.” Learning is done through supervised, unsupervised or reinforcement learning. Supervised learning necessitates a system to observe data, conduct analyses, and output to improve its understanding of the analyzed phenomenon (Bzdok et al., 2018; Kotsiantis et al., 2007). Unsupervised also uses statistical techniques which are suited to discovering patterns without outputs or interaction with another agent such as a human or other computer system (Hastie et al., 2009; Tarca et al., 2007). Reinforcement learning includes techniques where the computer agent is intended to explore a set of actions or situations and then learn or anticipate outcomes from different choice options (Sutton, 1992); the system learns the relationship between consequence and action (Chandak et al., 2019; Huang, 2021). A simple example of machine learning is an online application that learns purchasing habits and begins to make recommendations based on your own patterns and those of individuals like you.

Knowledge-based Systems (KBS). Knowledge-based systems are focused on using existing knowledge to enable computational decision making. This subfield aims to develop inferences about knowledge and enable user interaction to support, supplement or engage complex systems (Akerkar & Sajja, 2009). These systems may require constructed representations of knowledge (e.g. that use an ontology) with a particular focus on the relationship of the meaning of elements within the set of knowledge. A KBS is an agent that adapts or creates inferences (Bergmann et al., 2005) based on existing knowledge. While these systems have existed for some time, they are not as popular given newer development in AI (Abdullah et al., 2006).

Computer Vision. Computer vision may be one of the more popular known AI techniques within landscape architecture because of the subfield's pursuits of simulating human perception of visual elements (Szeliski, 2010). There are a range of approaches used in this subfield, with some of the more recent oriented toward machine learning approaches. Computer Vision focuses on pattern recognition (Chen, 2015) and object extraction (Prince, 2012). A popular tool landscape architects use is Google Lens, which can identify a whole host of plants using computer vision techniques.

Robotics. Robotics is centered on the use of sensors, often coupled with machine learning (often reinforcement) and computer vision, to automate tasks. Robotics can encompass technology such as autonomous vehicles (Faisal et al., 2019) and lawnmowers (Wasif, 2011), as well as systems to irrigate and weed agricultural lands (Talaviya et al., 2020). Robotics can serve to replace human actions but can also offer new forms of collaboration (Vrontis et al., 2022).

Natural Language Processing (NLP). Natural language processing is another subfield that focuses on learning language and then recreating it to generate meaningful responses or outputs. NLP uses a range of techniques to form an understanding of language, including grammar and lexicon, learning and language processing (statistical techniques), constructs and representation (meaning and action), and techniques to manipulate language and learn the appropriateness of those manipulations (Chowdhary, 2020).

Optimization. Optimization is another subfield within AI, that may often be misrepresented within landscape architecture. While designers often attempt to optimize a given space, or develop parametric models to aid in design, AI approaches necessitate some kind of learning or algorithm to support the optimization. An important lesson here is that AI approaches usually require a specific delineation of the problem in some quantifiable means. The techniques often associated with optimization in AI are usually associated with search algorithms (Mirjalili & Dong, 2020), such as genetic algorithms (Chamberlain & Meitner, 2009; Li et al., 2013), simulated annealing (Rutenbar, 1989).

Importantly for all the subfields identified, the quantitative expression of constraints, goals, inputs and outputs (when applicable) must be well defined. Fernberg and Chamberlain (Fernberg et al., 2021) state that nearly every application of AI requires creating ontologies, methods, data mining or expert-based learning and developing statistical approaches to facilitate reasoning and may be done explicitly or implicitly. While humans play a range of defining roles in AI, the key is that the machine is the learning agent. Learning happens, typically, with abundant data, a clear language, and a reliable set of rules to follow.

3 Methodology

This section lays out a protocol for implementing our systematic review. In it, we describe the process for searching, screening, and selecting literature that is sufficiently relevant to the research objectives. Landscape Architecture encompasses activities and processes from a range of disciplines. Many LA-related fields already have extensive AI-related literature reviews, such as urban forestry (César de Lima Araújo et al., 2021), urban design and planning (Abusaada & Elshater, 2021; L. Yang et al., 2022), transportation (Abduljabbar et al., 2019), land use planning (Chaturvedi & de Vries, 2021), horticulture (B. Yang & Xu, 2021), construction (Abioye et al., 2021) and a range of others. For this review, we narrowed articles to specific disciplinary keywords of Landscape Architecture, Design and Planning.

To be included in our review, articles must exist within a searchable English-based literature database. All years of publication were included, though the recency of AI in literature is relatively new (post 2000s). The initial literature search utilized three databases: Scopus, IEEE, and JSTOR. Each of these was chosen to provide expansive interdisciplinary coverage across the arts, humanities, and sciences—all of which are integral in some way to the landscape and AI fields. JSTOR and a digital humanities affiliate called Constellate were used to find landscape architecture industry insights, as JSTOR currently houses every issue of the official periodical for the American Society of Landscape Architects (ASLA)—currently operating with the moniker Landscape Architecture Magazine or LAM—from its first publication in 1910 up until 2015. The most recent issues of LAM, from 2016 to the present, were searched and screened using keyword searches on the publication website, URL https://landscapearchitecturemagazine.org/. Hence, SCOPUS was chosen as the main data source, while the others were used for full article download and data validation.

3.1 Search Strategy

The search terms comprised two lists, one encompassing all relevant AI techniques and methods (and spelling modifiers) and one representing what we deem to be core landscape discipline terms, organized into two single-line text strings then combined with the Boolean operator AND. These terms were adapted from previous literature reviews of AI (Abioye et al., 2021; Emaminejad & Akhavian, 2022; Tebyanian, 2020; Wu & Silva, 2010; Yigitcanlar et al., 2020) with some additional terms we added in order to be more exhaustive. We did not limit applications of AI. The combination is as follows:

Line 1 (AI Search Terms): “Robotics” OR “Computer vision”, OR “Machine learning” OR “Expert System” OR “Knowledge-based Systems” OR “Optimisation” OR “Optimization” OR “Natural Language Processing” OR “Artificial Intelligence” OR “K-Means Clustering” OR “Hierarchical Clustering” OR “Fuzzy Clustering” OR “Model-based Clustering” OR “Linear Discriminant Analysis” OR “Monte Carlo” OR “Deep Belief” OR “Deep Boltzmann” OR “Deep Learning” OR “Convolutional Neural Network” OR “Stacked Autoencoders” OR “Recurrent Neural Network” OR “Deep Neural Network” OR “Speech processing” OR “Evolutionary computing” OR “Evolutionary Algorithms” OR “Swarm Intelligence” OR “Discrete Optimisation” OR “Convex Optimisation” OR “Discrete Optimization” OR “Convex Optimization” OR “Automated Planning” OR “Ontology” OR “Automated Scheduling”

AND

Line 2 (Disciplinary Search Terms): “Landscape Architect*” OR “Landscape Design*” OR “Landscape Plan*”

Scopus initially returned 528 results and IEEE returned 67. The search query could not be effectively executed in the JSTOR database due to character limitations and a catalog method which returned too many irrelevant results. We attempted to custom code our search using URL hacks, but the results were still highly problematic. To ensure due diligence and not leave a resource entirely, we attempted a simple Boolean-limited search using “Landscape Architecture” and “Artificial Intelligence”. The initial return was >6000 results, and a quick browse of the first several dozens of these results found the included articles to be completely irrelevant to the topic. However, after doing an advanced search in which the publication title had to contain the word "landscape", we were able to narrow the results to a return of 56 articles, three of which contained a directly relevant subject matter (Lindhult, 1988; McCarthy & Portner, 1980; von Wodtke, 1988). While these articles are not included in the formal results of our systematic search, they will be touched on in the Discussion section. Furthermore, to account for other sources that may not have been included in the systematic search process, we investigated Google Scholar, Google. On Google Scholar and Google (web search) we used the same two Boolean-limited search terms as used with JSTOR. These did not result in any substantially different outcomes. Where possible, we included articles in the discussion.

3.2 Data Collection

Metadata and bibliographic information on the initial search results were exportable from all databases and done so in two ways. The first was to export the saved searches in .RIS format to Zotero reference management software, where each article's bibliographic information along with links to full text were organized into database-specific folders. The second data collection method was an export of the saved searches into .CSV files, one from each database. The data were then cleaned and combined into a common attribution structure joined into a single .CSV file, which served as the principal dataset for our review and analyses. A cleaned table of the data is included in Supplemental Materials.

3.3 Study Selection Coding

While the initial search returned a somewhat digestible literature chunk, it also returned many duplicates and articles which seemed irrelevant to the purposes of this review—either because the work did not constitute a true investigation of AI, did not utilize AI methods, or did not reasonably fall into the scope of landscape architecture/design or landscape planning, despite the use of the Boolean operators to narrow the search.

To decide whether a study met the inclusion criteria of the review, we created a Python script to further refine our master database. The code iterated through each item, by combining the title, abstract and keywords and then identifying the frequency of keywords used that matched our search terms. We used the same disciplinary search terms ("landscape architecture", "landscape design" and "landscape planning") and then separated each of the subfields of AI with their specific terms (each term listed was in quotes and shortened words utilized * for Boolean limiting):

- **Machine Learning**: machine learning, supervised learning, unsupervised learning, reinforcement learning, deep learning, k-means clustering, hierarchical clustering, fuzzy clustering, model-based clustering, linear discriminant analysis, monte carlo, deep belief, deep boltzmann, deep learning, convolutional neural network, stacked autoencoders, recurrent neural network, deep neural network;
- **Knowledge-based Systems**: knowledge-based system, expert system, intelligent agent, case-based reasoning, linked system, ontology;
- **Computer Vision**: computer vision, scene reconstruction, motion analysis, image restoration, recognition;
- **Robotics**: robotic, climbing, actuation, locomotion;
- **Natural Language Processing**: natural language processing, speech processing, text mining, text analy;

- **Optimization**: optimiz, optimis, discrete optimi, convex optimi, evolutionary comput, evolutionary algorithm, genetic algorithm, differential evolution, particle swarm, swarm intelligence.

The script then coded each literature with the number of instances each of the disciplinary terms and subfield keywords indicated in the matched fields, as well as a general search for "artificial intelligence." We further refined our data by eliminating any instances where no keywords were present. This process provided a validation of the database search, by offering complete control over the included literature. Further, as the script processed each literature row, it identified if a duplicate article was found using year + title, since a DOI was not always present. Duplicates were denoted in a separate file, then the authors manually confirmed and removed them (85 in total).

Once all literature was coded, we then manually coded all dissemination venues (journal, proceeding, book, etc.) for: 1) alignment to the disciplinary search terms and 2) review rigor of the dissemination venue. Alignment of the field consisted of journals that are predominately associated with the discipline, including adjacent journals or proceedings. For instance, venues primarily aimed toward computer science or engineering were considered a low alignment for LA. Further, review rigor was evaluated based on the reputation of the journal, including impact scores (factors, cite score, etc.) and the review process. Coded values included: 1 = high alignment and review rigor, 2 = combination of low/high or mid for both, and 3 = low alignment and review rigor. These dissemination values (1-3) were then referenced with each article. The full list of all venues and the tier scoring is provided in Supplemental Materials.

The resulting master dataset now provided a means to filter literature using:

- Appropriateness of the venue and review rigor;
- Alignment with one or more of the disciplinary terms;
- An AI-related keyword.

The results and trends provided are delineated from different filtering mechanisms used. The bulk of our commentary and detailed review of articles were from those with a score of 1 for appropriateness of venue and review rigor, which also matched at least one disciplinary and AI search term. These are referred to as *tier 1* articles. We reviewed each filtered result and coded them further across two additional criteria: degree of contribution and relevancy to the landscape search terms. For the degree of contribution, we coded one of the following:

- Mention: merely mentions a disciplinary and AI term
- Discourse: theoretical or commentary
- Application: applies AI technique or approach
- Creation: develops new technique or heuristic

For relevancy, we denoted if an article seemed central to activities or knowledge related to the landscape architecture discipline. There were instances where we recoded an article that may have had a landscape-oriented search term but was completely irrelevant to AI, or vice versa. Broader trends metrics include articles with a score of 2-3 for appropriateness of venue and review rigor. These articles were not reviewed in depth and are referenced as *tier 2* for the purposes of this literature review. Tier 2 does not necessarily mean the contribution is of less value, particularly if the article aligns primarily with other fields.

Further, we noted that articles with terms aligned with *optimization* were often not AI-related, instead using the term to describe other quantitative or qualitative techniques. When used quantitatively, optimization overwhelmingly referred to a linear or stochastic technique to optimize a space or design, typically with a set of environmental variables. Additionally, some optimization articles focus on parametric modeling with mentions of optimization, but again were clearly focused on the optimization of the model or design element without a coupled AI-approach. We anticipate that several articles in tier 2 may be aligned with optimization, but not with AI. After completing our search, we filtered all disciplinary results where optimization was indicated without any other AI keyword. We then read through all titles to identify potential articles that likely used AI techniques but may have not stated this explicitly or used a term that may have been missed by our search terms. Any article we suspected may have used AI-coupled approaches were flagged (roughly a dozen). Unfortunately, there precisely delineating the degree to which AI is embedded across all optimization articles is nearly impossible. This is because every article would need to be read in-depth (some of which are unavailable in full text) and others with substantial interpretation (many have inadequate documentation of methods).

4 Review Results and Trends for AI-LA Applications

4.1 Results of Literature Review

A total of 600 articles were identified that met both the landscape keyword requirement and the AI keyword requirement. These were published across over 300 different venues ranging from top-tier journals, conference proceedings, individual university publications and book publishers. Of the venues, 70 were tier 1 (priority for review), 31 were tier 2, and 207 were tier 3 (with 90% of those receiving the lowest ranking due to applicability to discipline and review rigor). Of the 600 articles that met the tier 1 filter, 31 were associated with keyword “Landscape Architecture”, 29 with “Landscape Design” and 150 with “Landscape Planning”, with ten of these overlapping more than two of these terms.

Upon reviewing all publications with keywords, the authors identified roughly one hundred articles that meaningfully apply to the discipline and AI simultaneously and represent the greater themes in the literature. The vast majority of these were application-based, with a handful of others oriented towards theoretical or speculative discourse and a very select few denoting a new advancement or creation.

4.2 Trends

The recent popularity and growth in AI-related works has been substantial. Figure 1 illustrates the rates of publication for each of the three disciplinary keywords. The figure shows publications from 2000 to the end of November 2022 for all literature that met both AI and disciplinary terms, as well as those literature published in top tier venues. As the chart indicates, publications with the term “landscape planning” emerged earlier and was consistently producing more than the other terms. While this is true for top tier venues, the trend has shifted recently with “landscape design” emerging with more publications when all non-disciplinary venues and lower tier venues were considered. From top tier venues, “landscape architecture” and “landscape design” seem to have a similar output frequency with the latter slightly higher. Broadly, the data show continued growth in the topic, with an extremely fast rise in publications when considered all venues.

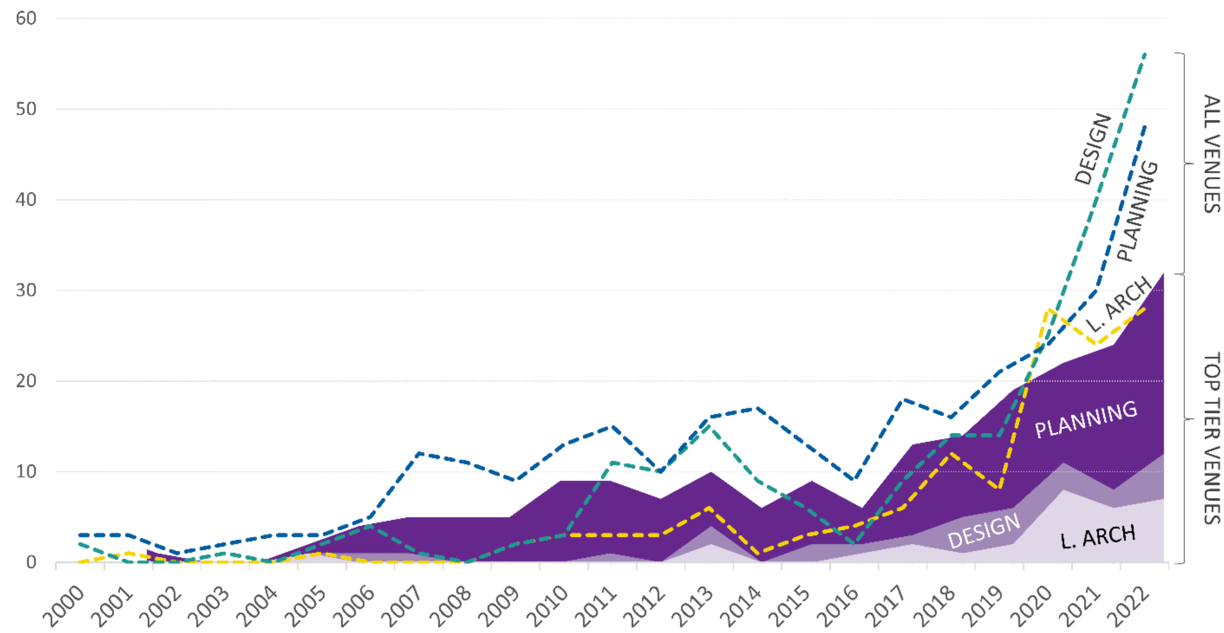

Figure 1: Publication Counts of All Matching Keywords that met both discipline and AI keywords (2000-2022). Lines show the results across tier 1 ranked dissemination publications (darker lines) and All tiers (lighter colors). X-axis is count of publications.

Across all three terms, there were 12 publications before 2000, with the first in 1978 that used a multiple hierarchical clustering method to help create a database of natural resources for assessment and planning (Frondorf et al., 1978). The articles during this time period were focused on database development, computer vision techniques and impact assessment. Some were methodological (primarily within computer science venues) and other were applications (primarily environmental journals). After 2000, there was a gradual increase in published works, with the majority of works being published in the five years. In general, publications have continued to rise across the umbrella landscape terms, with a significant drop during 2014-2016. The most rapid rise has come since 2016.

It should be noted that in our review, the terms landscape design and planning incorporated very broad definitions, with landscape design incorporating projects of a range of areas, while planning was typically oriented toward larger areas. It was also more apparent that both landscape design and landscape planning were terms used in other disciplines when they wanted to mention how their development or application of AI might align with other disciplines. We noted that landscape architecture was not used as frequently in mentions, even though the discipline does conduct both design and planning across scales.

We also identified author country affiliation across all publications. In total, we found 791 counts of country affiliations (meaning numerous articles were partnerships with scholars of more than one country). Twelve countries were identified as having more than 10 affiliations across all tiers, those countries are shown in Figure 2. Over one-third of the world's countries, with representation from all continents, have published something related to our search terms (67 countries). A full list of all affiliations is included in the Supplementary Documentation. The rapid rise of AI-related publications across all tiers seems to emerge broadly across the world with Chinese scholars leading this effort. It is important to recognize the substantial diversity of projects and venues where authors publish – and the proportion of tier 1 to all tiers differs substantially by country. Of the top 20 countries affiliated two thirds have about half of the publications in a tier 1 venue, with over half of all countries publishing at least fifty percent of articles in tier 1 venues. The overall trend indicates a growing interest in AI globally, which may represent a likely increase in funding related to this work, the expertise necessary to operationalize AI within the disciplines and partnerships being formed across disciplines.

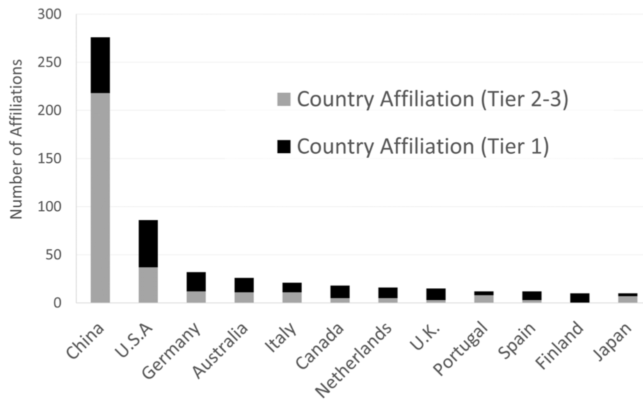

Figure 2: Author Country Affiliations showing the difference of affiliations by tier ranking.

4.3 AI Subfield Prevalence

We conducted an analysis of the distribution of AI techniques within the discipline (landscape architecture, design and planning). The analysis observed all 600 publications that returned one or more matching disciplinary keywords and AI keywords (including "artificial intelligence"). Since artificial intelligence is not a single technique, for the purposes of reporting here, we eliminated any article that did not mention one of the subtypes of AI. There were 62 instances where only "artificial intelligence" was used as a keyword without any other subtypes indicated as a keyword. Of the 538 articles remaining, there were 597 total keywords instances where one of the AI keywords was used (indicating several articles with more than one AI subtype keyword included). The distribution of the subfields is provided in Figure 3.

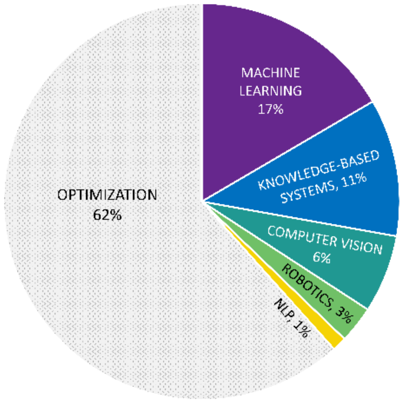

Figure 3: AI Subfield Distribution Counts of All Matching Keywords (discipline and AI)

Figure 3 demonstrates the vast proportion of works involve machine learning and optimization, a pattern which mirrors that of other AEC industry disciplines (Abduljabbar et al., 2019; Abioye et al., 2021). We investigated our data further, counting not only whether an article mentioned a subfield, but also the total frequency of mentions of keywords. It is difficult to make inferences about the meaning of the frequency of word use, but there is a slight increase in the use of optimization and machine learning relative to the other subfields. This is likely because most recent AI advancements have been within the realm of machine learning or optimization, though this is quickly changing as fields natural language processing, robotics, and computer vision are making exponential progress (Malone et al., 2020).

As we acknowledged earlier in the Methods, the keyword search for optimization overestimates the number of contributions to literature in artificial intelligence because optimization is a term that can be used qualitatively and parametrically where automated learning is not central to the process but could be replaced with a stochastic or recursive algorithm without learning. Subsequently, without having access to full text for all articles, we conducted a review of titles and keywords manually to identify instances where optimization was clearly indicating an AI technique. We found less than 5% of the optimization articles fit this criterion, but even after reviewing articles we could access in full text, it was not always clear if their methods were actually AI because of limited documentation. As such, we have visualized, in Figure 4, the distribution of all non-optimization techniques to emphasize the role of three primary techniques used in the field. Likewise, the distribution of these subtypes through the years (starting in 2000) is provided in Figure 5. This distribution shows a trend in the subtypes that are associated with publications, suggesting machine learning and computer vision applications have grown almost tenfold, whereas the other subtypes are dropping in proportion. This is likely due to the increasing availability of tools and training scholars are using, as well as the a natural shift away from other techniques (Abdullah et al., 2006).

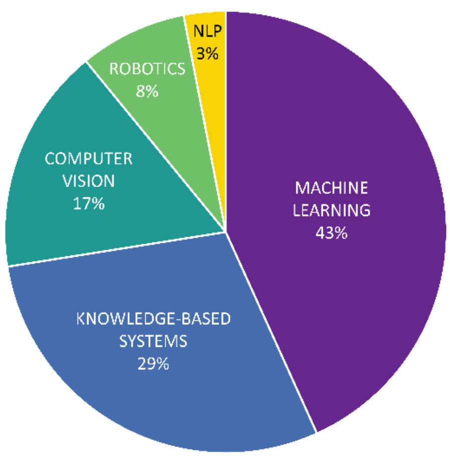

Figure 4: Subset of AI Subfield Distribution Counts of All Matching Keywords (discipline and AI)

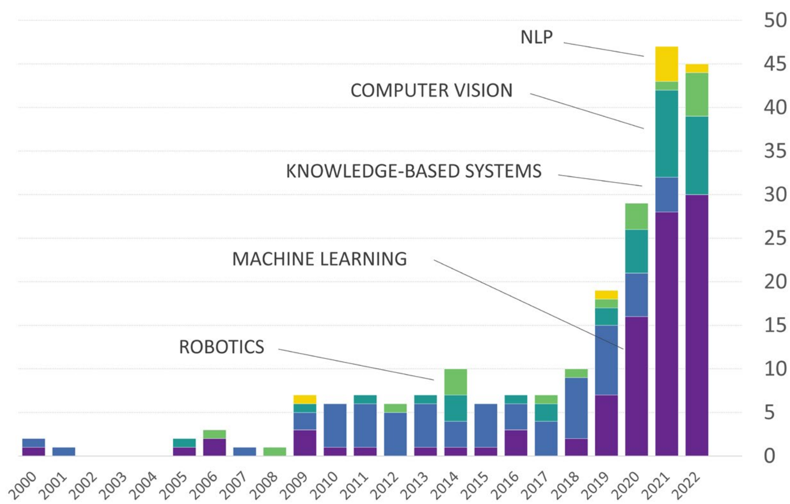

Figure 5: Temporal distribution and use of different subfields of AI from Figure 4 (only showing 2000-2022)

4.4 Salient Themes in AI-LA Research and Practice

A close reading of the literature reveals significant themes in AI-LA knowledge work. These themes range from a fine-grained focus on optimizing aesthetics or design process to using self-improving algorithms for large-scale ecological modeling and forecasting, to analyzing policy efficacy and public sentiment of open spaces through natural language processing. They are as follows.

Design generation and evaluation. AI-driven applications for landscape design are proliferating rapidly as landscape practitioners are learning how to extrapolate the technology to improve design process and products. The review illustrates this occurring across a range of scales, from Zhang et al.'s computer vision driven classification method for design details of Suzhou-style private gardens (2021) to Naderi and Raman's decision trees for pedestrian landscape designs (Naderi & Raman, 2005), to a slew of academics and professionals' use of machine learning for generating concepts at the urban scale (Koma et al., 2017; Raman et al., 2022; Slager & De Vries, 2013). There is also an emerging trend of AI applications for design evaluation, ranging from improving machine perception of greenery (Suppakittpaisarn et al., 2022) to the use of computer vision, machine learning, and optimization techniques for post-occupancy evaluation of user experience and ecosystem services in public open spaces (Schlickman, 2020; Wael et al., 2022; X. Wang, 2021; J. Yang et al., 2022). Outside of the results found in academic databases, our web searches revealed an abundance of AI-powered design applications being introduced or operated. Some are directly relevant to landscape design, such as Autodesk and Sidewalk Labs' tools for urban landscape design (Harrouk, 2020; Hickman, 2020); while others are more general but have potential use and impact for design. These include apps like NVIDIA Canvas, which allows users to make rough, color-coded brush strokes and instantly iterate them into landscape renderings of various styles (Tack, 2021) and AI-powered text-to-image generators like Midjourney, DALL-E 2, or Stable Diffusion, which create conceptual renderings from user-generated text strings (Brezar, 2022; Dreith, 2022; Monge, 2022).

Perhaps the most obvious pervasion of AI applications into landscape architecture and design workflows will be through the already burgeoning computational design ecosystem. In 2017, Proving Ground introduced LunchboxML, one of the first published plugins for machine learning in the Grasshopper/Rhino3D environment (Miller, 2017), and a slew of ML plugins have proliferated since. The following year, Cantrell and Mekies assembled a group of leading professionals and academics to conjecture the role of parametric and computational design in landscape architecture in a series of essays (2018), some of which anticipated a prompt pervasion of AI applications into design (Ervin, 2018). The review results combined with perusal of non-academic sources suggest such anticipation to be accurate, and also suggest the need for a better way of documenting the phenomenon.

Ecological modeling. Computational ecology has been prolific in the AI literature, and the field's methods have begun to creep into modeling applications tooled for landscape design and planning purposes. For instance, Zhang and Bowes trained ML models that outperformed typical models in real-time predictions of groundwater table response to storm surge in Coastal Virginia (2019), and in turn posited a more machine-driven landscape monitoring regime. Abdollahi et al. (2022) devised a new optimization approach to modeling urban ecosystem service zones based on landscape patterns. On the other side of the urban-rural transect, Benke et al. introduce a sophisticated application of geovisual analytics (driven by agent-based modeling) to model the movements of ruminants in the landscape using satellite tracking data. While possibly not central to the discipline as of yet, the concept of using advanced modeling to predict patterns of grazing animals over large landscapes could be useful to consider as part of a design process. This is especially true for animals that may use intentionally-designed large areas. Taking the idea of machine-driven management further, Goodwin et al. (2022) and van Strien and Grêt-Regamey (2022) both introduce ML methods for classification of landscape typologies. Taken with the other autonomous management methods, a provocative question arises of whether AI utilization could foster a land management regime that is entirely automated from start to finish.

There are also significant AI developments in forest planning and management. Salient examples from the review include techniques to optimize (here we cite AI-optimization) for timber harvest (Eyvindson et al., 2018; W.-Y. Liu & Lin, 2015), land use modeling (Lin et al., 2009), habitat-specific restoration (Westphal et al., 2007), measuring forest connectivity (Peng et al., 2019; Shanthala Devi et al., 2013) and spatial design of forests (G. Liu et al., 2006); machine learning applications for species distribution modeling (Alegria et al., 2021; Ngarega et al., 2021); modeling and planning for effects of fire in the forest landscape (Miranda et al., 2020; Stamou et al., 2016; Zema et al., 2020); and modeling complexities of varied forest landscapes (Ask & Carlsson, 2000; Gärtner et al., 2008; Hummel & Cunningham, 2006). These works represent only a sample of what has been done in Forestry—the discipline has been prolifically producing optimization methods in recent decades (Kaya et al., 2016) and AI has creeped significantly into urban forestry (César de Lima Araújo et al., 2021)—but are representative of the research authors deemed relevant to landscape planning or design, whether in titles or keywords.

Predictive analytics. Simulation and forecasting are another obvious anecdote for trending methods in landscape and spatial planning, and the review gives evidence for it. Subjects cover anything from using gaming technology, agent-based modeling (ABM) and AI to simulate potential pedestrian and social life in urban spaces (Almahmood & Skov-Petersen, 2020) to forecasting climate and emissions scenarios at the landscape scale (Bergier et al., 2019; Ngarega et al., 2021), optimization for estimating green infrastructure potential (Dong et al., 2022), and landscape simulations for improving predictive forest management (Hummel & Cunningham, 2006; Kampichler & Sierdsema, 2018; Stamou et al., 2016). While predictive analytics only had a handful of results falling under the umbrella term of “landscape planning”, the fact that they are among the most common methods in AI-driven urban planning, internet of things (IoT) or Smart Cities conceptualizations (Souza et al., 2019) makes them very relevant to the landscape disciplines, as many decisions and models will inevitably creep into the operational territory of a landscape architect or planner focused on urban environments.

Landscape policy evaluation. A number of studies utilized AI methods to model ecosystem services. For instance, Groot et al. used evolutionary algorithms for generating planning and design solutions for multi-functional landscapes (2018); Queiroz et al. used k-means clustering to map and classify ecosystem services bundles (2015); while others modeled socio-ecological determinants, associations, or natural capital stocks and flows associated with ecosystem services

(Lorilla et al., 2020, p.; Mouchet et al., 2014; Zank et al., 2016). Other projects utilized AI as part of evaluating landscape policy outcomes (both potential and actual). These include Berkhardt et al., who used machine learning to generate land use classifications from remote sensing imagery in order to measure conformity to and impacts of water conservation measures; Wang et al.'s Monte Carlo simulation technique to measure cooling and energy saving potentials of shade trees and urban lawns in Phoenix (2016); clustering methods for prioritization of green corridor development (Shapira et al., 2013); and development of machine learning tools for maximizing biodiversity benefits in conservation planning (Thomson et al., 2020).

Sentiment analysis and social media. Sentiment analysis (SA), or sentiment modeling, is a burgeoning research area that uses text and image data mining and to understand public opinion of issues, services, or social phenomena, among other things (L. Zhang & Liu, 2017). The methodology has grown precipitously over the last decade and pervaded across a wide variety of fields, mostly due to the abundance of user data generated in social media (Yue et al., 2019). The landscape and urban design disciplines are included in this creep (C. Yang & Liu, 2022), and review results suggest future growth as public engagement methods evolve among researchers and practitioners. Much of the work to date centers around public green space satisfaction. Song et al. utilized computer vision (including face and object detection models) to analyze and annotate imagery captured from social media platforms to inventory and assess characteristics such as temporal patterns of park use, social dynamics, activities, and demographics (2022). Jahani et al. applied artificial intelligence techniques to identify the prevalence of bird sounds in urban green spaces and their association with mental restoration (2021). Ghermandi et al. extracted online geolocated photographs from social media platforms then used computer vision cloud services to characterize human-open space interactions in urban green spaces (2022).

Wang et al. zoomed out to a regional scale as they employed machine learning techniques to assess green space satisfaction of 50 parks in Beijing (2021). They also introduced a landscape-feature lexicon to help improve granularity of landscape sentiment analysis. Other studies focus on measuring sense of place in important cultural or touristic landscapes such as the Las Vegas Strip, USA (Song et al., 2021) or Mt. Huangshan, China (Chai et al., 2021), or on simply understanding discrepancies between policy measures and user experience using natural language processing of user-generated text data (Wartmann et al., 2021).

Knowledge systems for AI-LA applications. Another less prolific but important grouping of studies are theoretical or speculative pieces touching on the permeation of AI methods into landscape practice and the need to formulate knowledge frameworks that help designers and planners adapt to it. Zhang provides a historical sketch of cybernetic environments, positing that landscape designers have previously had influence on their development and should reclaim that influence to drive the future (2020). Cantrell et al. argue through synthesis of current developments that AI's fast-growing influence presents an epistemological crisis for landscape architecture and that the profession may need to rethink its authorial role in solving wicked problems of the day (2021). In accordance with this frame, Fernberg et al. suggest addressing the crisis involves formalizing operational language into ontological frameworks for AI systems (2021) and that there is a need to grow more systematic knowledge of AI in landscape architecture. Exemplary efforts to do so include Tebyanian's review and primer for machine learning in urban landscape design (2020) and Ervin's history and taxonomy of digital landscape architecture, which gives historical context to computational developments and associated progression in landscape architecture while providing commentary about terminology and definitions—including one of the first references in the literature to the concept of 'bionic' landscapes (2020).

5 Discussion

In carrying out the review process, the authors drew some distinct impressions of the state of AI in landscape architecture. Broadly, sentiment toward AI within the field is growing rapidly. This is depicted by the diversity of AI-based implementation across all publications, the global distribution of work and likely the recognition of the importance of design from within more computationally centric fields. Yet even amongst the most non-technical, discipline-focused venues for landscape architecture, planning, and design, there appears to be an uptick in publications. Further, the sophistication and implementation of AI methods may demonstrate the increased training and access to techniques that are being afforded researchers, as well as funding opportunities globally. Importantly, researchers within the discipline who are interested in AI should become aware of the vast interest from other disciplines who want to engage in the discipline, in particular being aware that much of the growth in the topic is associated with the term "landscape design". More broadly, we reflect on Fernberg and Chamberlain (2019) who ask about the role technology specialists might play within the future of landscape architects. To what extent will landscape architects (here we speak more broadly toward designers and planners as well) develop and embrace AI taking agency on how it is implemented within the discipline, or will technology designers from outside the discipline shape the discipline using AI?

It is important to underscore that the while scope of this review focuses on direct relevance to the umbrella terms "landscape architecture", "landscape design", and "landscape planning", the breadth and depth of AI-related research increases significantly with the inclusion of terms or activities that could feasibly fall under the umbrella of the landscape architecture discipline but have greater relevance or recognitions in allied fields or disciplines. For example, research advancements of automation in agriculture and ecology are longstanding, and now converging to offer unique solutions to global food security problems. Researchers have seen success in applications ranging from vegetation biomass and cover estimation in fire-damaged landscapes (Anderson et al., 2018), measuring forest tree defoliation using smart-phone photos (Kälin et al., 2019), or using image-based deep learning models for disease detection in agriculture (Mohanty et al., 2016) to thermal mapping waterbodies, forest monitoring, and aerial seeding using UAS (Amorós & Ledesma, n.d.; Hogan et al., 2017; Minařík & Langhammer, 2016; Novikov & Ersson, 2019; Sai et al., 2020; Vovchenko et al., 2020). Combining artificial intelligence (AI) applications in agriculture with emergent methods in agroecology shows the potential to address pressing problems in 21st century food systems such as climate change uncertainty, optimizing data flows, or crop efficiency (Barbieri et al., 2018; Cherkauer et al., 2018; Leippert et al., 2020). Most if not all of these applications have some relevance to landscape architecture or landscape planning—as some designers work in agricultural contexts or are interested in applications for ecological restoration in their site planning—but the subjects of the studies in and of themselves may not be considered central to the practices, teachings, or research of landscape architecture.

Another interesting area of convergence that may appear less obvious is in robotics. While the literature search only returned one article on robotics in the landscape disciplines—Westort and Shen's exploration of robot-assisted, in-situ landscape gardening (2017)—the authors see robotics as an emerging theme. The exponential growth of robotics in the AEC industry as suggested by Abioye et al. (2021) and Emaminejad and Akhavian (2022), the man established architectural robotics labs (*International Map of Robots in the Creative Industry*, n.d.), and an uptick in landscape-oriented robotics projects from institutions such as Louisiana State University and ETH Zurich (Harmon et al., 2022; Hurkxkens et al., 2020, 2022; Johns et al., 2020)—projects not picked up in the literature search because of term mismatch—there is clear evidence that this subfield of AI has potential for an outsized impact on the landscape disciplines, particularly design.

While a distinction between relevant AI research in agriculture or robotics and landscape design is fairly intuitive, the line becomes thinner when considering fields like urban design and urban planning, which overlap significantly with landscape disciplines in interests, theory, and methods (Van Assche et al., 2013). For instance, there are a number of extensive and already highly cited reviews of artificial intelligence in urban planning subjects such as land planning dynamics (Wu & Silva, 2010), planning for smart cities and big data (Allam & Dhunny, 2019; Yigitcanlar et al., 2020), transportation planning (Abduljabbar et al., 2019), and urban forestry (César de Lima Araújo et al., 2021; Nitoslawski et al., 2019). All of these have direct relevance to landscape design in urban contexts but would be otherwise unknown in a review that only includes the keywords "landscape architecture," "landscape design," or "landscape plan"—which could in turn mean hundreds of informative studies on landscape-relevant AI applications go unnoticed from parochial scoping in terms.

Furthermore, the same dilemma applies to the more specialized terms of landscape architecture. If, for example, a reader would rely on the current study which focuses more broadly on the discipline, they would consider AI development to be overwhelmingly nascent with just a few dozen relevant studies. But if they were to perform a search using "stormwater management," one of the specializations of which licensed landscape architects are required to have some knowledge, they would find an abundance of well-established literature on AI applications for stormwater plans (Imran et al., 2013). In the authors' view, this exercise paints a complicated picture wherein the vast majority of contributions to AI development relevant to landscape architecture come from researchers and practitioners outside the discipline; a paradox where AI-LA research and practice is at once established and emerging, quite possibly to the ignorance of many in the profession in either sense. Such a notion suggests that practice-based researchers should be aware that using only discipline-specific terminology in precedent research could unintentionally blind them to relevant information if they are too parochial in keyword usage. On the other hand, a more robust output of AI-LA research from within the discipline could bolster the relevance of its lexicon and help to avoid constant borrowing and fitting of knowledge from outside it. In other words, the knowledge domain unique to landscape architecture could effectively build a new appendage that relates to AI and its use in practice and scholarship.

Given these limitations, we suggest that future work can more comprehensively illuminate the role of AI in landscape research and practice by expanding the scope of the research and utilizing a broader but systematic lexicon of disciplinary terms. For example, a future study could include a full-scale systematic literature review that takes the current work's AI search terms protocol and queries literature using established disciplinary frameworks such as the Landscape Architecture Body of Knowledge (LABOK Task Force, 2004) or the core landscape knowledge domains developed by Langley et al. (2018). Doing so could likely provide a more encompassing panorama of AI-related work that includes the facets of the profession that clearly fall under its purview but do not always carry the labels of "landscape architecture", "design", or "planning". Besides expanding the terminology, future AI-LA reviews or other investigations should also seek to bridge the knowledge accessibility gap between academia and practice. While the current work illustrates practice-driven AI research and applications as published in the industry standard Landscape Architecture Magazine and white papers from a handful of practice-based research labs, the question of how to appropriately (and systematically) compile knowledge from industry and synthesize it with academic literature remains largely unsolved. A protocol for addressing this problem will provide mechanisms for consistent and defensible longitudinal research on AI's transformations of the profession in coming decades.

As part of this special issue in Landscape Journal, we set out to explore how artificial intelligence has and is influencing landscape architecture, design, and planning. In conducting this review one of the more difficult decisions was selecting the bounds of a discipline, that is, by definition, rather interdisciplinary. Those reading this article are likely to have read and most certainly will read articles from a variety of different disciplines that relate or conduct research on landscapes. In many contexts the definitions of architecture, design and planning within landscape often blend, especially when referenced from outside the discipline. Ironically, in our search we not only discovered the increase in AI-related publications within these fields of study and practice, but a significant body of literature published in venues and by authors outside of these disciplines that give mention to their potential contribution to one or more of these three landscape terms. However, the wide range of different publication venues cataloged from our search and ranking techniques makes it difficult to ascertain the role AI might play within the discipline in the future. This is because most of the articles associated with the discipline come from lower tier venues where stated relevance to practice and research are vague.

The question of what defines landscape architecture, or landscape design or landscape planning is an ontological and socio-cultural question. In our section, "Terms" of Landscape Architecture we provide some context for why we set out to identify these three terms and to ascertain the contribution of AI within these narrower definitions of what these fields practice. We discovered an increasing trend of AI-related publications in venues central to these disciplines and that the rapid rise of this work has surged in the past few years. From within landscape architecture the rise has only increased recently. For instance, in the 2022 issue of the Journal of Digital Landscape Architecture, the authors identified several new publications that applied artificial intelligence techniques, with some of those being direct applications and others referencing the significance of the techniques (Barbarash et al., 2022; Fengjing et al., 2022; Khalilnezhad, 2022; X. Liu & Tian, 2022; J. Yang et al., 2022).

One of the significant challenges of this research endeavor was identifying if and to what extent AI is playing a role in practice and education. Most literature reviews, including our own, often focus on peer-reviewed publications, or at a minimum, dissemination products that show up in literature related databases. Unfortunately, outside of Landscape Architecture Magazine (LAM) and the LAF Case Studies repository, there are not any obvious centralized venues for publishing practice-oriented work, at least in the US. While LAM has published AI-related articles (Cantrell, Ellis, et al., 2017; Fernberg & Chamberlain, 2021; Petrich, 1986; Zeiger, 2019), these are limited in number and primarily contributions from academic scholars. We ask whether or not this is an indication of the lack of AI-related work being conducted in practice or if there is a knowledge and dissemination gap. As discussed in emerging themes, we are aware of several efforts from landscape architecture practice involving AI applications, but these contributions are not being included in searchable databases. Such a lack of compilation can make identifying contributions from practice very difficult and limit the democratization of these works, even if that is not the intent.

It is at the intersection of disciplinary recognition, ontology and the dissemination of works from the fields identified that we see a conundrum. Does landscape architecture, design and planning play a key role in proliferating or at least applying AI-related work? Are scholars within the field publishing in other disciplinary journals and not giving credit to the contribution to their field or is dissemination not taking place, or is there really a limited amount of work? In any case, we argue that researchers and practitioners should consider including search terms that relate to the broader landscape disciplines, while also including AI-related keywords in abstracts and metadata associated with publications. This may help to raise awareness of the contributions within the field and bring greater recognition to the application of these techniques to other disciplines, as well as make this information more readily available to students, practice and scholars. A specific example of this could be the use of the term “landscape design”. Interestingly, it appears the overwhelming increase in publications across all venues is associated with this term but come from venues outside the discipline. Further, in the articles we reviewed that used this term, we noticed that it often serves as a catch-all that might be more appropriately delineated as landscape architecture or landscape planning. Thus, in an effort to promote our own disciplinary contribution toward AI, future publications may want to consider adding ”landscape design” to keyword searchers where publications are AI centric. This may increase the likelihood of knowledge sharing within and outside landscape centric disciplines. When considering the general pulse of publications across all venues, the relative growth and access of AI-related techniques shows plausible continued growth of AI-related articles.

6 Conclusion

After reviewing hundreds of articles, websites, books, and proceedings, we believe our observations can be reasonably summed up in three important takeaways:

1. Interest and contributions toward AI are growing steadily and significantly in the landscape discipline, both in academic research and professional applications.
2. Applications and discourse from all subfields of AI have grown exponentially over the past three years. This, in our view, suggests the emergence of a new technological paradigm for the discipline.
3. Landscape researchers in all sectors (e.g. academia, practice, government) would be well served to formalize, compile, and contribute to a clear AI-LA knowledge framework and/or AI-LA standards of practice to ensure proper workforce preparedness (whether in pedagogical or professional settings).
4. To promote AI knowledge sharing across all disciplines, more universally accepted terms (e.g. landscape design), should be included in AI publications within the discipline.
5. The need for scholars and practitioners to improve the democratization of knowledge sharing by ensuring publications are indexed and easily accessible (e.g. open-source) from a variety of databases (e.g. Google Scholar, Scopus).

Engagement with technology driven by artificial intelligence, both practically, speculatively, and critically, is increasing year over year in landscape architecture, design, and planning, and will continue to do so. This literature review is the first attempt at providing a formal epistemic baseline for said engagement and incite a more systematic approach to compiling the knowledge it produces. As artificial intelligence systems continue to permeate everyday landscape practice, the workforce will have to confront a number of adaptive challenges. How and where do we integrate AI into existing design and planning processes? Do those processes fundamentally change because of said integration? How will landscape practitioners ensure that the AI systems mediating their workflows are producing socially and environmentally equitable outcomes? We argue that such questions can only be answered if there is a formal framework for understanding how AI has, does, and will affect the state of practice. The review shows evidence that AI-LA knowledge is nascent even if rapidly growing, hence current gaps in the literature could be reasonably identified or filled with a more systematic method for measuring AI's influence in the more detailed subsets of landscape disciplines, especially one that bridges dissemination gaps between academia and professional practice. If researchers, professionals, and educators act now to develop this protocol, it could serve as leverage for landscape to take the lead in shaping a techno-vernacular of the future. If we hesitate, we run the risk of causing unnecessary root shock to the profession because of failure to get ahead of the next technological tipping point AI is pushing us towards.

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