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Towards intelligent land administration systems: Research challenges, applications and prospects in AI-driven approaches

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A B S T R A C T

Due to emerging sustainability and resilience issues, particularly in rapidly urbanising areas, managing land information necessitates more effective approaches by adopting innovative digital and intelligent technologies. Many land administration systems (LASs) worldwide still rely on manual and rigid methods, resulting in inadequacies and inefficiencies. Alternatively, artificial intelligence (AI) has received significant attention in (geospatial) information systems. However, adopting AI in LASs is a major challenge from technical, legal, and institutional perspectives. This study investigates current approaches for AI applications across four critical land administration functions: tenure, value, use, and development through a review of the body of knowledge. The main contributions include offering a comprehensive overview of current AI developments in land administration, outlining critical research challenges, and providing future visions in AI-driven LASs. The review indicates the full potential of AI across the entire landscape of land administration has not yet been fully realised, with certain areas still in the early stages of adoption and facing significant challenges. Moreover, AI has been utilised across various discrete research areas. Therefore, this research introduces a conceptual framework for building intelligent LASs using AI-driven approaches. Its novelty lies in aligning with the land information management paradigm, whereby AI is holistically integrated into the land administration functions to enhance consistency. Furthermore, the framework's two layers show how the functionality of LASs depends on the robustness of data infrastructure powered by AI technologies. Ultimately, the framework supports the shift from static record-keeping to more responsive and data-driven LASs.

1. Introduction

Managing information related to land, the surface of the earth and any asset below or above it, holds a unique and critical importance. This is because land is fundamental to economic development, environmental sustainability, and social well-being across all countries and jurisdictions (Dale and McLaughlin, 2000; Williamson et al., 2010). Land information can be viewed through diverse analytical lenses and theoretical frameworks for various purposes in different domains. However, the fundamental perspective is how land, a finite resource, is governed. Land administration systems (LASs) provide an operational environment for implementing land policies and strategies using their four core functions, including tenure, value, use, and development (Williamson et al., 2010; Rajabifard et al., 2019), working together to promote land administration to achieve sustainability and resilience. Indeed, LASs are responsible for the collection and sharing of information related to the ownership, value, and use of land in support of land policy implementation (Europe, 1996). Basically, the functionality of LASs relies on the effectiveness of the management of the data as critical inputs for their execution. Therefore, land information infrastructure (LII) constitutes the central core of LASs, providing a foundation for the management of land administration data using suitable technologies.

The lifecycle of land administration data comprises different phases (Saeidian et al., 2023), including:

- *Data capture:* Initially, boundaries of land parcels, as the basic land units, and properties, vertically aboveground or underground, are first delineated precisely using different surveying and data acquisition methods. Subsequently, the value and usage of these land parcels and properties are determined using valuation models and land use planning regulations. 2D/3D survey plans, legal documents

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such as deeds and titles, appraisal reports, and land use maps are all examples of the generated output from this phase.

- *Data validation*: Following data capture, the quality of the captured data needs to be assessed and verified using validation rules, ensuring that the data does not include any possible semantic or spatial errors, such as overlaps between land parcels (Asghari et al., 2020).
- *Data modelling*: Data models provide a structured approach to modelling attributes and relationships in data elements required for managing land administration data, facilitating data manipulation, visualisation, and query analysis (Aien et al., 2011).
- *Data storage*: In this phase, land administration data, both semantic and spatial, is stored either file-based or in cadastral databases (Shahidinejad et al., 2023).
- *Data visualisation*: This phase is essential for providing a spatial representation of land parcels and properties that can potentially help understand the land administration data, particularly within complex spaces, using various platforms (Shojani, 2014).
- *Data sharing and query*: Finally, data is disseminated to a wide range of stakeholders via data portals, using different tools such as digital twins. Stakeholders can perform different query analyses for various use cases, such as retrieving ownership boundaries (Barzegar et al., 2020; Atazadeh et al., 2019).

However, current traditional LASs are characterised by inadequacies and inefficiencies in communicating and managing land administration data, particularly in complex urban environments. These systems currently focus on data maintenance in digital formats (i.e., registration of land records), as completeness and digitalisation are the primary priorities in many countries and jurisdictions. While countries like New Zealand have achieved near-complete registration of land records, most of the land in many countries, exemplified by Kenya, has not been registered yet due to ineffective land administration data management (Bennett et al., 2019). In India, as of 2017, only 47 percent of mutation records reflected current ownership (Mishra and Suhag, 2017), with 40 percent of disputes related to land (Thakur et al., 2020), which underscores the need for real-time record updates. In Indonesia, as of 2020, about 30 percent of land parcels remained uncertified, while many faced issues with duplicate certifications (Rahim et al., 2024). In Pakistan, as of 2023, inefficiencies and the complexity of the LAS often caused delays in resolving land disputes in civil courts (Ullah and Hussain, 2023), which highlights the need for predictive and preventive solutions. Moreover, procedures in most land administration organisations are usually manual and time-consuming, and there is no clear procedure for managing land administration data over its lifecycle (Kalogianni et al., 2020). For instance, the conversion of one single paper/PDF-based survey plan into digital formats via the *ePlan program* (Cumerford, 2010) in the state of Victoria, Australia, requires an average processing time of two weeks (Olfat et al., 2018).

Although different information technologies, such as geospatial information systems (GIS) and blockchain, have been integrated into LASs, current systems typically use static databases and rule-based workflows, which makes them rigid. However, more responsive systems are required as modern land administration faces dynamic and complex challenges. Hence, LASs can go beyond simple digital record-keeping and be able to reason, adaptively learn, and predict to support decision-making. This underscores the urgency of adopting intelligent approaches to transform LASs from passive systems into active and responsive ones. For example, when a complex right, such as a 3D easement, is going to be traced to identify the relevant beneficiaries and affected land parcels and properties aboveground or underground, substantial effort is often required. This is because data is highly fragmented within different documents and databases, which makes it neither easily accessible nor queryable. Hence, an intelligent approach is required to understand and link the data and decide, preventing delays and further costs in land administrative practices.

Artificial intelligence (AI) has been identified as one of the most powerful operational drivers that can be leveraged for managing land administration data (Jahani Chehrehbargh et al., 2024; Sagandykova et al., 2024; UNECE, 2021). Although AI has no globally accepted and unique definition, it is generally enabling machines to mimic different aspects of human intelligence, empowering machines to adjust to new circumstances, and performing human-like tasks (Russell and Norvig, 2016; Duan et al., 2019). A wide range of techniques that can broadly be categorised into rule-based and data-driven paradigms are used for replicating different aspects of human intelligence. The main aspects of AI are:

- *Reasoning*: It refers to the process of human-like logical thinking. Rule-based systems, such as expert systems, are based on explicit knowledge, which is represented in the form of encoded if-then rules by human experts. In uncertain situations, tools such as Bayesian networks and fuzzy logic are employed to effectively handle uncertain knowledge (Gupta and Nagpal, 2020). This aspect has significant potential to support the decision-making process, bringing more transparency but less adaptability.
- *Learning*: It refers to the process of human-like knowledge acquisition through experience and adapting to new situations. Machine learning, as the core of the data-driven paradigm in AI, enables computers to learn from experience in the form of data, build a model, and make predictions with the model. This process is undertaken by feeding learning algorithms with experience data during the training phase and making predictions for new data during the testing phase. Decision trees, random forest (RF), support vector machine (SVM), k-means, and density-based spatial clustering of applications with noise (DBSCAN) are all popular examples of machine learning models that can be categorised into supervised and unsupervised models. Supervised models are trained on labelled data and can be categorised into classification models for discrete outputs and regression models for continuous outputs. Unsupervised models, on the other hand, group unlabelled data and are potentially appropriate to provide data insights (Zhou, 2021). Deep learning, a subset of machine learning, simulates the structure of the human brain and can automatically extract deep patterns from data through its multi-layer neural network (Guangqi, 2024; Bengio et al., 2017). Compared to reasoning, learning has more adaptability but less transparency.
- *Cognition*: Beyond reasoning and learning, computer vision and natural language processing (NLP) attempt to replicate human cognition aspects such as vision and speech. The role of computer vision is to enable computers to perceive, interpret, and understand visual information for various purposes, such as feature extraction from imagery plans. On the other hand, NLP seeks to recognise, understand, and generate information in the form of human language, such as textual addresses (Nishant et al., 2020).
- *Problem-solving*: It refers to the process of identifying potential solutions and selecting an optimal solution based on its potential to achieve the desired goal. Heuristic and metaheuristic techniques, such as evolutionary algorithms, are prominent examples of search strategies that are widely used for optimisation purposes (Michalewicz, 2013).

AI technologies offer three main capabilities. It enables automation, supports real-time functionality and prediction, and enhances decision-making. These capabilities can be employed in different domains based on their respective purposes to have an intelligent environment that transforms raw data into informed decisions. A prominent domain in which AI has transformative applications is geospatial science. This has resulted in the emergence of the specialised field known as geospatial AI (GeoAI) that applies AI techniques to analyse and interpret geographic data (Li and Hsu, 2022). GeoAI develops and uses algorithms to analyse and interpret geospatial data, enabling advanced insights into geographic phenomena as a wide range of impactful applications across various domains, including infrastructure planning and development, environmental conservation, disaster preparedness and response, precise agriculture, as well as smart transportation systems. Specifically, the adoption of AI into land administration, as a subdomain of geospatial science, can result in streamlining workflows, processing large volumes of land and property information, and decreasing cognitive load to facilitate decision-making. Land administration functions and AI aspects are shown in Fig. 1.

Regarding the adoption of AI in the land administration domain, pinpointing the exact first use of AI in land administration is challenging. Nonetheless, the conversion of paper-based land records into digital systems, coupled with the integration of land information with other computer-based technologies such as GIS for creating a spatial data infrastructure (SDI), is recognised as the early beneficial influence of computers in the field (Williamson et al., 2010). However, these benefits are basic computational and logical operations and do not involve higher-order human intelligence such as learning, perceiving, and communicating. Although AI technologies have been gradually employed across various areas related to land administration, their potential advantages have yet to be fully realised, and significant research challenges persist. Moreover, an overview of the current state of the adoption of AI in the land administration functions domain is notably sparse and has not been sufficiently explored. This paper investigates current approaches for AI applications in the land administration domain, aiming to provide a holistic view of how AI technologies are currently applied to support different land administration functions. This study covers both symbolic and sub-symbolic AI, with a primary focus on emerging technologies in sub-symbolic AI, including machine learning and deep learning (e.g., neural networks), NLP (e.g., text classification and large language models (LLM)), and computer vision (e.g., image classification and optical character recognition (OCR)). Accordingly, the fundamental research question that this paper aims to answer is: *How is AI currently transforming information management for four critical land administration functions: land tenure, value, use, and development, and how can its future adoption advance land administration data management?*

In response to this question, this research addresses three research objectives:

1. *To investigate the current state of AI in LASs:* Achieving this objective offers a holistic perspective by investigating the current body of knowledge in AI applications for land administration data management.
2. *To explore current research challenges in the adoption of AI in LASs:* This study identifies the challenges that researchers and industry practitioners face when applying AI in land administration practices, including not only technical limitations related to data but also regulatory and institutional issues.
3. *To develop future directions for AI-driven LASs:* In this research, innovative opportunities and effective responses to the current challenges are outlined. Proposed future directions are beneficial in transitioning towards intelligent LASs driven by AI technologies.

The remainder of this paper is structured as follows: Section 2 illustrates the methodology employed for this review. Section 3 and its subsections provide a thorough overview of the current AI-related research in land administration to address the RO1. In Section 4, a conceptual framework and phased road map for integrating AI and LASs has been proposed. The discussion in Section 5 focuses on the research challenges and future directions relevant to RO2 and RO3. Finally, the conclusion is drawn in Section 6.

2. Review methodology

The review has been undertaken through a methodological framework, encompassing three main stages, which are depicted in Fig. 2.

First, in the literature retrieval stage, an initial pool of relevant papers has been retrieved from data repositories using appropriate keywords in AI and land administration contexts. Scopus, as one of the world's most extensive abstracting and indexing scholarly databases, was selected for its frequent updates (Burnham, 2006; de Moya-Anegón et al., 2007). It has broader coverage than Web of Science (Pranckutė, 2021) and more advanced search functionality than Google Scholar's basic search. Moreover, it has a higher score of retrieval relevance compared to newer platforms like Dimensions (Singh et al., 2023). A query was executed in the advanced document search part of the Scopus database, in which keywords that are the most repetitive words in land administration and AI contexts were used, which is illustrated in Table 1. Some filters were applied in which we restricted our search to "*Articles*" and "*Conference papers*" and restricted the language to "*English*". We searched documents within "*Article title, Abstract, Keywords*". The keywords were used in the form of a "*loose phrase*" in which double quotation marks (") are used. As some keywords may have multiple variations (e.g., cadastre and cadastral, network and networks, and processes and processing), we used a wildcard (*) to capture all forms of the keyword. Overall, 511 documents were obtained.

Then, the papers were filtered to exclude non-relevant papers by screening titles and abstracts. Finally, the full text of the remaining

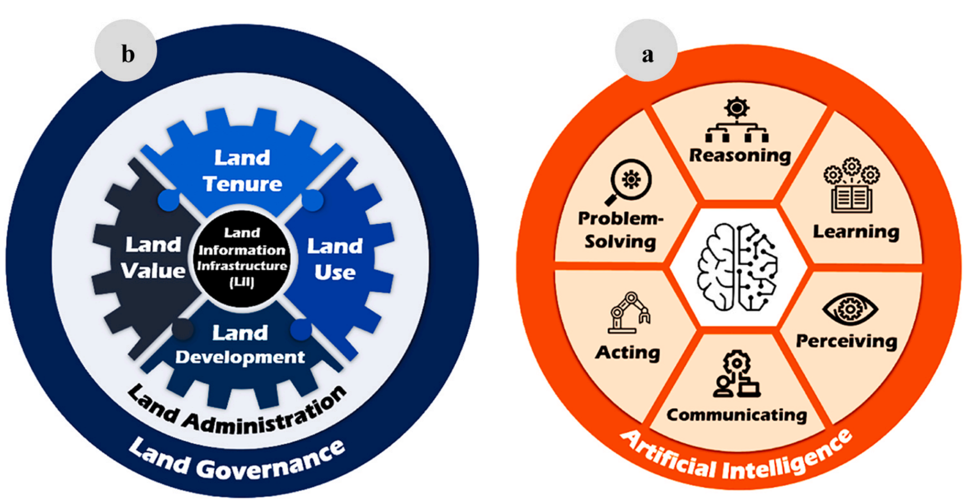

Fig. 1. How can different aspects of AI (a) be applied to support the functions of LAS (b)?.

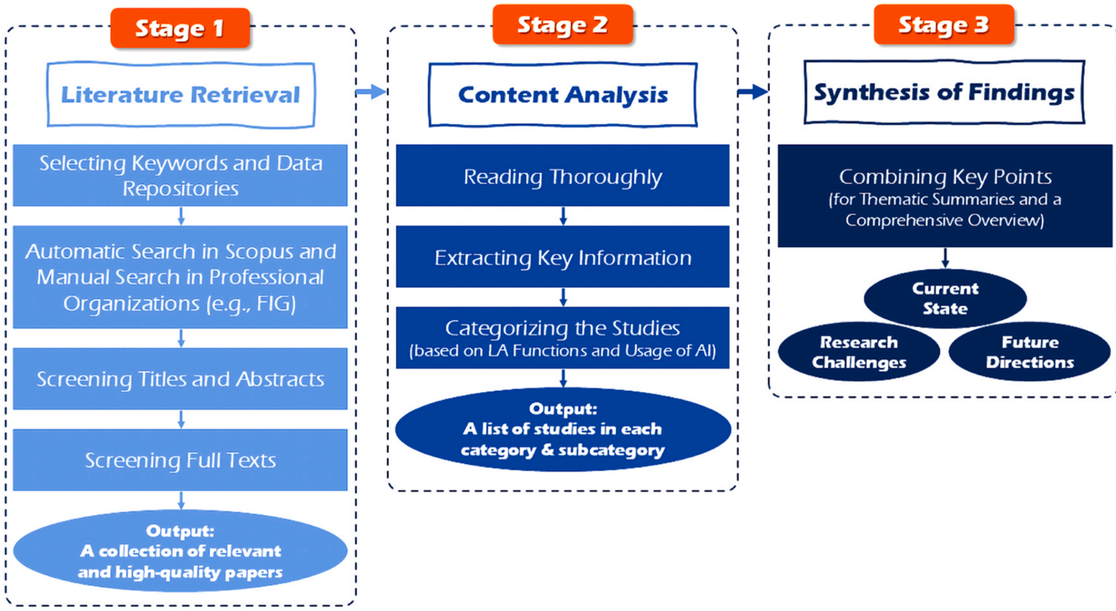

Fig. 2. A methodological framework for literature survey.

Table 1
Keywords used for searching in Scopus within stage 1.

Category	Keywords
Land administration	land administration, cadastr*
AI	AI, artificial intelligence, big data, data mining, pattern recognition, anomaly detection, predictive analy*, agent system*, intelligent agent*
Problem-solving	problem solving, heuristic* search*, metaheuristic* search*, adversarial search*, evolutionary algorithm*, genetic algorithm*, swarm intelligence
Reasoning	logical reasoning, case-based reasoning, reasoning system*, knowledge representation, knowledge graph*, knowledge-based system*, rule-based system*, expert system*, uncertain knowledge, fuzzy set*, fuzzy logic, fuzzy inference, fuzzy system*, Bayesian network*, decision network*
Learning	learning algorithm*, learning model*, learning system*, machine learning, deep learning, reinforcement learning, transfer learning, supervised learning, unsupervised learning, neural network*, support vector, decision tree*, random forest, gradient boosting, long short-term memory, generative adversarial network*, k-nearest neighbour*, k-means
Perceiving	computer vision, image process*, object recognition
Communicating	language model*, natural language process*, natural language generation, generative pre trained transformer, speech recognition, voice recognition, text analy*, question answering, machine translation, semantic interpretation
Acting	robotic*

papers has been screened to find high-quality papers for subsequent stages. The screening process was conducted using Rayyan® which is an online tool that efficiently helps filter irrelevant papers based on set criteria and labelling them, resulting in a more organised and clean collection of papers. Moreover, to make sure that no relevant papers were missed, Litmaps® was applied to create a visual citation map and identify any overlooked seminal papers. Ultimately, 244 papers were included in the final selection, and their publication year distribution is shown in Fig. 3.

Next, in the content analysis, the selected studies are thoroughly reviewed to extract key information such as land administration function, land administration practice, contribution of AI, the used AI techniques, methodology, limitations, and outcomes. To support author keyword analysis, VOSviewer® was used to visualise and categorize keyword occurrences in the selected papers, which is illustrated in Fig. 4. Studies are then categorised based on their focus areas, providing a holistic overview of the application of AI in different current land administration practices. In this regard, Visual-Paradigm® was employed to create a Sankey diagram for illustrating the relationships between aspects of AI and land administration functions. In the final stage, synthesising the findings, identified key points have been combined to create thematic summaries, leading to pinpoint challenges and future directions. Table 2 shows a summary of quantitative metrics obtained during the first two stages of the methodological framework.

3. Current AI-related research in land administration

In this section, we present a comprehensive snapshot of how AI technologies are currently applied to support different land administration functions. This overview establishes a cohesive understanding of the existing body of knowledge and enables us to examine the extent of AI applications in each land administration function. As a result, this examination clarifies the current state of research, leading to identifying research challenges and guiding future directions within the field in the next section.

Current AI-related research in land administration has been categorised based on land administration functions and their subcategories. Each function of land administration plays a uniquely significant role in administering land parcels and properties, each having its own distinct legal boundaries, ownership, value, and usage. The boundaries of land parcels and properties, vertically under or above the ground, with their associated legal rights, restrictions, and responsibilities (RRRs) are delineated by the land tenure function that is essential for securing rights, promoting stability, and facilitating transactions. The assessment of land and property values, as well as the determination of taxation obligations, are in contrast, undertaken in the land value function that is vital for providing an equitable and sustainable land market that benefits all stakeholders. The land use function focuses on the regulations and strategic planning for controlling land utilisation. The land development function, on the other hand, refers to the process of designing and constructing new physical infrastructure.

The dynamic nature of tenure, value, and usage associated with land parcels and properties requires continual data management and analysis. This is because of frequent changes that occur over time, leading to the adoption of different technology-driven approaches. In the

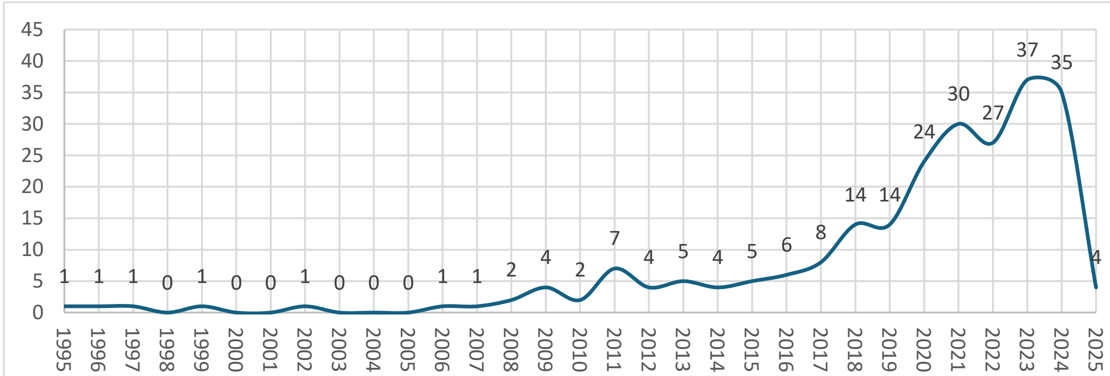

Fig. 3. Publication year distribution of the selected studies.

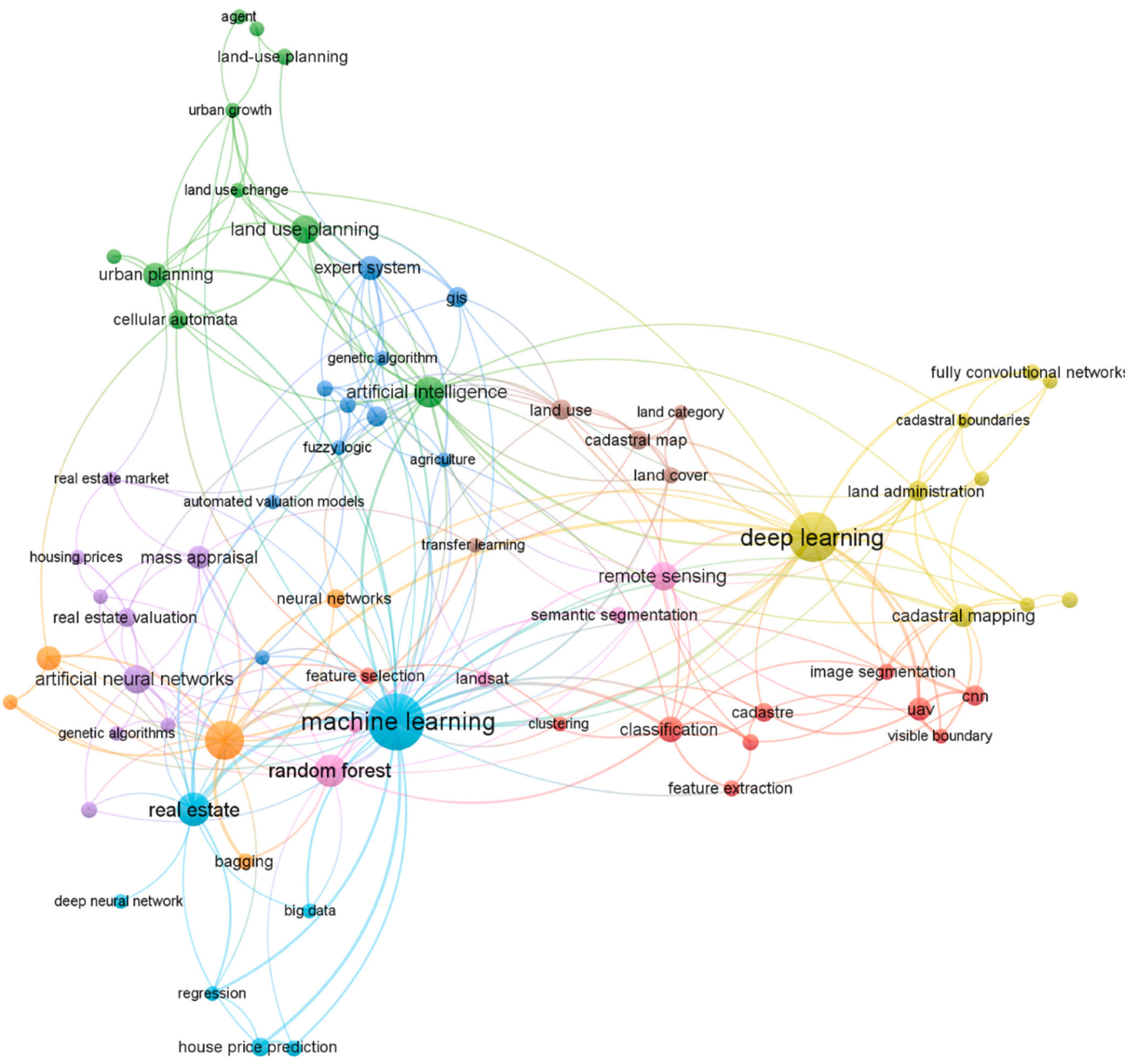

Fig. 4. Co-occurrence network of author keywords from the selected studies.

Table 2
Quantitative metrics obtained during the first two stages of the methodological framework.

Stage	Metric		Value
Literature Retrieval	Number of initial keywords used		65
	Initial pool of papers retrieved		511
	Papers selected after screening		244
	Author keywords appearing > 3 times		70
	Sources with > 2 papers		34
Content Analysis	Distribution by Land Administration Function	Land Tenure (12 sub-categories)	55 papers (22.5 %)
		Land Value (11 sub-categories)	85 papers (34.8 %)
		Land Use (15 sub-categories)	84 papers (34.4 %)
		Land Development (8 sub-categories)	20 papers (8.2 %)
	Frequency of AI Aspects	Learning	192 papers (78.7 %)
		Computer Vision	84 papers (34.4 %)
		Reasoning	31 papers (12.7 %)
		Problem-Solving	20 papers (8.2 %)
		Agent-Based Modelling (ABM)	14 papers (5.7 %)
		Natural Language Processing (NLP)	6 papers (2.5 %)

subsequent sections, current AI-related research has been summarised and synthesised in the following sections, explaining their contributions to the advancement of land administration. The connection between land administration functions and aspects of intelligence in the studies is illustrated as a Sankey diagram in Fig. 5. It illustrates the distribution of AI methods that are applied to each land administration function, in which the width of each flow shows the relative number of studies identified in this review. It is evident that learning is the most used aspect of intelligence in the functions, with significant application in land value, use, and tenure functions, followed by notable use of vision in land use and tenure functions. The widespread application of learning and vision in land use and tenure functions originates from the extensive use of spatial imagery and cadastral documents. Moreover, reasoning and agent-based modelling (ABM) are less common but especially support land use function. On the other hand, NLP appears to be the least utilised. This indicates that the application of NLP remains at an early stage of development within the land administration domain, that exploring the untapped capabilities of NLP in processing land-related data can be recognised as an emerging opportunity for future research.

3.1. *Land tenure function*

Land tenure refers to the processes of recording and registration of the legal extent of RRRs associated with land parcels and properties, ensuring secure access. This includes critical activities such as cadastral mapping and legal surveys for delineation and periodic updates, document analysis, reallocation of land parcels within the land subdivision and consolidation processes, land validation within the land registration process, as well as dispute resolutions. The following sections explain AI-related research within these contexts, with a summary presented in Table 3.

3.1.1. *Boundary delineation*

The first critical step in land administration is delineating the legal boundaries of land parcels and properties, which forms the basis for the next administrative activities. Traditional methods to precisely delineate boundaries of land parcels and properties need surveying measurements using tools such as total stations and legal documents such as plans of subdivision or consolidation. However, these methods are time-consuming and labour-intensive, which may not be precise enough due to limitations in measurement techniques. AI has demonstrated its capabilities to overcome these drawbacks.

Researchers are increasingly interested in using convolutional neural networks (CNNs) as one of the most common deep learning models. CNNs are, in fact, computer algorithms well-suited for image recognition tasks due to their capability at identifying spatial features and patterns in high-resolution remote sensing images. They are used to accurately

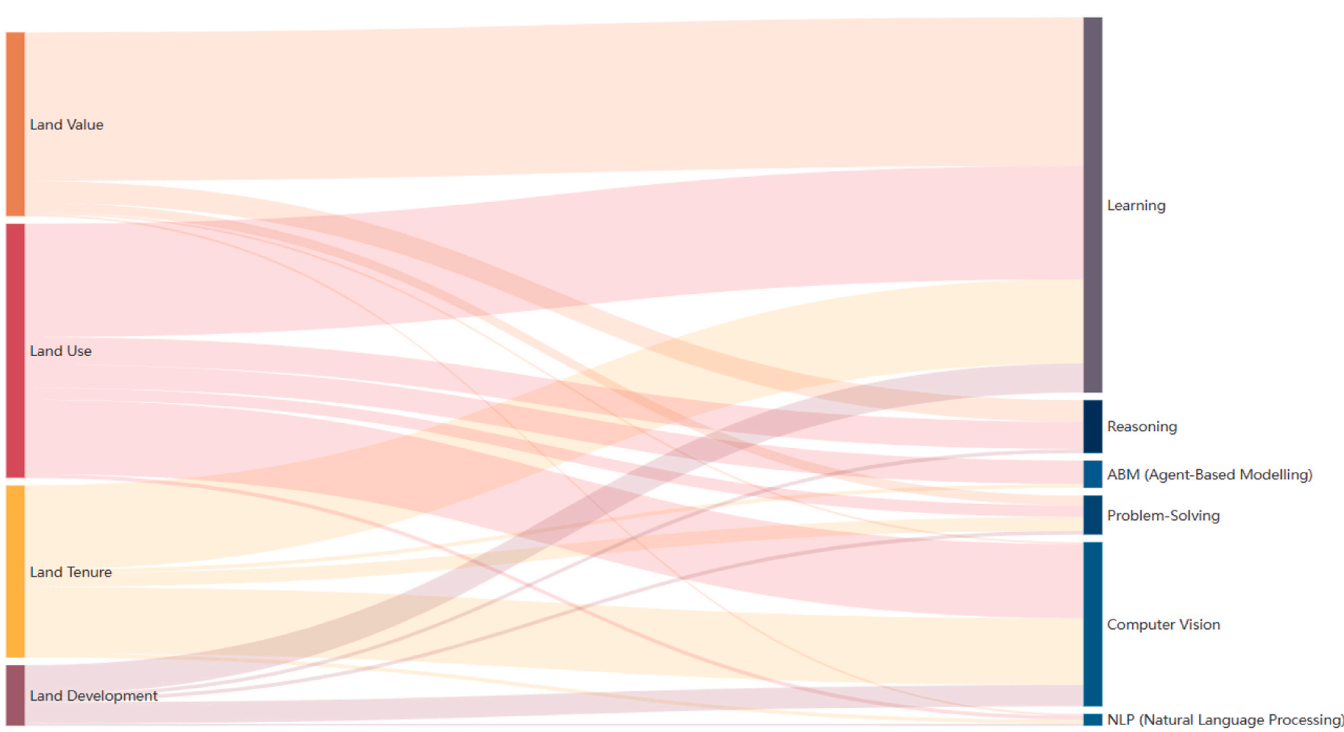

Fig. 5. Connection between land administration functions and aspects of intelligence in current AI-related research.

Table 3
Categorized overview of AI-related research in the land tenure function, with application areas and the objectives of using different AI techniques.

Application area	Focus area	AI model/algorithm/ technique	Description and objective of using AI	Studies
Boundary delineation	2D - using remote sensing data	CNNs (e.g., FCN, RCNN, and YOLO (You Only Look Once))	To extract visible boundaries of land parcels using remote sensing data (e.g., UAV images, Satellite images, and LiDAR)	(Fetai et al., 2021), (Xia et al., 2019a), (Kuchkorov et al., 2021), (Crommelinck et al., 2019), (Aung et al., 2020), (Xia et al., 2019b), (Fetai et al., 2020), (Tareke et al., 2023), (Khadanga and Jain, 2021), (Wierzbicki et al., 2021), (Kim et al., 2024), (Tysiac et al., 2024), (Abeho et al., 2024), (Metaferia et al., 2025)
		cGANs		(Khadanga and Jain, 2023)
		RF		(Metaferia et al., 2023), (Crommelinck et al., 2018), (Metaferia et al., 2025)
	2D - using IPS data	ANN	To extract property boundaries using UWB-based IPS	(Jiang et al., 2021)
	2D - using textual address data	NLTK (Natural Language Toolkit) Python library	To convert texts showing land parcels' address and dimensions to coordinates	(Odumosu et al., 2023)
	3D – using IPS data	CNNs, LSTM, and Bayesian network	To extract property boundaries using BLE-based IPS	(Potsiou et al., 2020)
		LSTM		(Potsiou et al., 2022)
Cadastral map revision and enrichment	Revision	CNNs (e.g., U-Net)	To extract visible land parcels boundaries using remote sensing data (e.g., UAV images, Satellite images, and LiDAR) and compare with existing cadastral maps	(Jovanović et al., 2021), (Zorzi et al., 2020), (Zampieri et al., 2018), (Fetai et al., 2022)
		XGBoost		(Dahle et al., 2021)
		Bilateral Attention Network (BANet)		(Li et al., 2025)
		Segment Anything Model (SAM)		(Vafaeinejad et al., 2025)
	Enrichment	RF and SVM Genetic, grey wolf, and Harris Hawks algorithms	To classify land parcels' boundary and select feature; To optimize hyperparameters	(Hajiheidari et al., 2024)
	Accuracy Improvement	GA	To improve spatial accuracy of land parcels	(Shnaidman et al., 2013)
Cadastral document analysis and digitization	Information extraction	ANN	To extract, convert, and digitize information from cadastral data into other formats	(Marcial et al., 2013)
		CNNs (e.g., U-Net and L-CNN) and RNNs (e.g., LSTM)		(Lenc et al., 2021), (Mango et al., 2023), (Lenc et al., 2023), (Franken et al., 2021), (Lindner et al., 2023)
		OCR		(Rosa and Garrido, 2019), (Yıldız et al., 2021)
		DNNs		(Ignjatić et al., 2018), (Petitpierre and Guhennec, 2023)
		ACCA BimAI®		(Tana et al., 2024)
		FrEX (Frame Entity eXtractor)	To identify key information in legal documents	(Salvaneschi et al., 2020)
		k-means, gaussian mixture model (GMM)	To identify and correctly extract cadastral boundaries and land parcels	(Ahmed et al., 2024)
Land reallocation in consolidation and subdivision	Optimization	GA	To find optimal reallocation	(Sahebgharani and Wiśniewski, 2024), (Teijeiro et al., 2022), (Ferreira Neto et al., 2011)
		ABC		(Özbeyaz and İnceyol, 2023)
		Decision trees, GBRT, LSTM, and ABM	To model government decision-making and to simulate farmers' decisions to participate, reflecting their dynamic preferences	(Herrera-Benavides et al., 2024), (Zhao et al., 2024)
		Fuzzy logic	To normalize data and address uncertainty in quantitative data	(Cay and Iscan, 2011)
		Fuzzy logic and expert systems	To assess the quality of land parcels for urban renewal projects to improve objectivity and fairness in the reallocation process	(Kilić Pamuković et al., 2020)
		GA and expert systems	To allocate land parcels to blocks based on landowner preferences and block size and to refine the allocation and minimize overflow or residual areas within blocks	(Haklı et al., 2018)
Influential factors in different specific tasks	Dispute intensity prediction	BCT	To find the most impactful factors	(Shin et al., 2021)
	Citizen satisfaction with land registration	SVM and RF		(Doan, 2022)
Land registry	Land parcel classification	SVM, GBT, multi-layer perceptron (MLP), Decision trees, RF, and extra trees	To classify land parcels based on their provenance information	(Kaffes et al., 2020)

extract visible boundaries of land parcels from the images, achieving accuracy rates exceeding 95 percent in some cases (Fetai et al., 2021). U-Net architecture is effectively applicable to learn and distinguish boundaries from the background of the images due to its symmetric encoder-decoder design. More specifically, to handle complex aerial and satellite imagery for detecting cadastral boundaries in agricultural fields and segmenting farmland, mask region-based CNNs (R-CNNs) and fully convolutional networks (FCNs) have been investigated. In addition, researchers proposed a specific benchmark dataset for cadastral boundary delineation, enabling them to train large deep learning models (Grift et al., 2024). Moreover, conditional generative adversarial networks (cGANs) have been used in some studies for extracting visible boundaries from unmanned aerial vehicle (UAV) images (Khadanga and Jain, 2023). cGANs are advanced computer algorithms that learn to create or improve images based on certain conditions, specifically when annotated data is scarce. Detected boundaries could be refined by integrating CNNs with techniques like oriented watershed transform (OWT), which helps to divide the image into clearer regions, to generate more precise polygons representing cadastral parcels (Xia et al., 2019a). However, using CNNs for analysing remote sensing imagery has been explored to extract only 2D boundaries. Besides remote sensing data, the conversion of textual descriptions of land parcels into spatial representations (e.g., polygons) using NLP is another research that has been conducted and can be applicable to systematic land titling (SLT) in peri-urban regions, in which the user can write the location and dimensions of land parcels in the form of text and then receive a converted polygon (Odumosu et al., 2023).

To delineate 3D boundaries of properties, researchers have applied machine learning and deep learning techniques for analysing data gathered from indoor spaces using volunteered geographic information (VGI) and crowdsourcing techniques as a reliable cadastral data source. In these studies, techniques like long short-term memory (LSTM) networks are used to process received signal strength indication (RSSI) from indoor positioning systems (IPS) devices like Bluetooth low energy (BLE) and ultra-wideband (UWB). LSTMs are algorithms designed to model temporal sequences and retain long-range dependencies, and are effective for remembering patterns over time, like tracking changes in signals. The position of a mobile device is then estimated in 2D and 3D, allowing property boundaries to be marked more accurately (Potsiou et al., 2020, 2022). Although CNNs are also employed for estimating indoor positions (Potsiou et al., 2020), bidirectional LSTM networks have demonstrated better performance in terms of accuracy. However, these approaches are useful only for fit-for-purpose land administration with a simple, basic, and affordable approach.

3.1.2. Cadastral map revision and enrichment

Upon the completion of the delineation of boundaries of land parcels and properties with their associated RRRs, they may need to be periodically revised and enriched due to changes in their tenure over time. In fact, land records need to be maintained up-to-date to ensure accuracy and reliability, addressing challenges like legal disputes over boundaries. In this regard, AI techniques have been utilised in some studies to enhance the level of automation of tasks such as boundary change detection and map enrichment. Researchers have developed deep learning techniques that align cadastral maps with remote sensing images to correct misalignments. CNNs with U-Net architecture have demonstrated accuracy in delineating boundaries of current data with minimal training data while still achieving high accuracy, offering a faster and more cost-effective alternative to traditional manual approaches. Gradient boosting, specifically extreme gradient boosting (XGBoost), which is an algorithm designed for classifying images and making predictions by analysing large datasets, has demonstrated efficacy in classifying changes by analysing attributes extracted from remote sensing data. This can potentially enable the identification of newly constructed buildings as well as those that have been demolished and modified. Fast execution time, low resource usage, and built-in mechanisms to prevent overfitting are recognised as the advantages of XGBoost that make it powerful for handling large datasets (Dahle et al., 2021). In addition, in some other studies, researchers have used machine learning algorithms, such as SVM and RF, to classify changes in parcel geometries between outdated and current maps by matching parcels using gravity centres, aiming at enhancing the automation of cadastral map enrichment. Problem-solving techniques like genetic algorithm (GA), grey wolf optimisation (GWO), and Harris Hawks algorithms have been used to optimise the hyperparameters within these studies (Hajiheidari et al., 2024). Overcoming the Least Squares adjustment, which has limitations for reinstating cadastral boundaries, by GA is also shown by researchers (Shnaidman et al., 2013).

3.1.3. Cadastral document analysis and digitisation

Various documents, such as survey plans, are frequently used within land tenure activities. In many countries or jurisdictions, these documents are still in a paper-based form, which needs to be digitised. Document analysis and paper-based data digitisation within the land administration context is, in fact, extracting information from the documents and converting them into digital formats to enhance accessibility. Employing different neural network models, AI can facilitate the detection of parcel boundaries as well as text existing in the documents. Detection of lot numbers using artificial neural networks (ANNs) (Marcial et al., 2013), landmarks and border lines using FCNs (Lenc et al., 2021), measurements on sketches using R-CNNs (Franken et al., 2021), and parcels with their numbers using a line convolution neural network (L-CNN) and ResNet-50 (Mango et al., 2023), are all examples of the application of deep learning models in cadastral documents analysis and digitisation. While ANNs have been considered due to their capabilities for pattern recognition tasks, FCNs are suitable for dense pixel-wise prediction. On the other hand, L-CNN and ResNet-50 have been used due to their robustness in feature extraction and sensitivity to linear features, which are common in cadastral plans. Using OCR in the conversion of abstract of field records (AFR) files, which are cadastral documents containing survey information of land parcels and properties, into land eXtensible markup language (LandXML) files and also for extracting the temporal dimension of cadastral parcels (Rosa and Garrido, 2019) are other studies that have been explored by researchers. Despite challenges such as the need for robust training datasets, researchers have demonstrated the power of computer vision combined with neural networks to automate and expedite the transformation of paper-based cadastral data into digital formats.

3.1.4. Land reallocation within land consolidation and land subdivision

Land reallocation is recognised as redistributing land parcels to enhance functionality. It involves land consolidation, in which fragmented parcels are merged into an integrated parcel, and land subdivision, in which large parcels are divided into smaller ones to support new physical developments. It is an optimisation problem. AI techniques for problem-solving, such as genetic (Sahebgharani and Wiśniewski, 2024; Teijeiro et al., 2022; Ferreira Neto et al., 2011) and artificial bee colony (ABC) (Özbeyaz and İnceyol, 2023) algorithms, have been investigated by researchers to automate the optimisation of land reallocations by considering factors such as shape, size, value, and access. Additionally, to incorporate landowner preferences for making decisions more subjective, fuzzy expert systems have been developed in some studies (Kilić Pamuković et al., 2020; Haklı et al., 2018). Recently, gradient boosted regression trees (GBRT) and LSTM algorithms have been used for constructing data-driven agent-based models, which are computer simulations where individual agents (people or entities) interact based on data. Its aim is to simulate the behaviours of stakeholders in the decision-making process for identifying potential rural residential areas for land consolidation (Zhao et al., 2024). While GBRT is well-designed for identifying complex nonlinear relationships between attributes and decisions, LSTMs are suitable for handling sequential patterns in time-series data. Hence, the combination of these models leads to a more realistic simulation of the decision-making process. Overall, managing complex scenarios by these methods can strongly overcome combinatorial problems within the land reallocation process and mitigate the effects of uncontrolled land redistribution.

3.1.5. Land validation within land registration

Following the land recording process, the quality of the recorded data must be verified before registering them within the land validation process. The provenance of a finalised land parcel polygon representing the last version of initial polygons from various registries is often missing in cadastral databases due to the lengthy and incremental nature of cadastral procedures. Regarding this, a classification model for polygons based on machine learning algorithms has been developed for predicting the provenance of land parcel polygons by analysing their geometric attributes and relationships. Several spatial features, such as area, boundary length, number of vertices, mean and variance of edge lengths, and centroid distances, have been used for training the machine learning model in which the gradient boosted trees (GBT) have shown their superior performance (Kaffes et al., 2020).

3.1.6. Influential factors analysis in different specific land tenure activities

3.1.6.1. Prediction of dispute intensity. AI techniques have been applied to predict the intensity of ownership disputes within multi-owned buildings (MOBs). In fact, researchers have found that ownership and architectural factors can potentially impact the intensity of disputes. In this regard, to identify the most impactful factors, machine learning techniques such as boosted classification tree (BCT) have been employed to make a level classification of factors, resulting in specifying six factors such as the design of common properties that need to be critically addressed during the planning stages of MOBs to minimise disputes and their negative consequences (Shin et al., 2021).

3.1.6.2. Citizen satisfaction with land registration. Another application of AI in influential factors analysis is examining citizen satisfaction with land registration procedures. A study has been conducted in which SVM and RF algorithms have been used to analyse many interviews with citizens based on various administrative procedure evaluation metrics. RF was selected as it can potentially handle high-dimensional data and rank the importance of features, which helps identify key drivers of satisfaction. On the other hand, SVM was selected because it may be able to manage smaller datasets and effectively classify satisfaction levels using subtle textual and numerical indications. The findings show that the frequency of required visits to administrative offices and waiting times are the two most impactful factors in citizen satisfaction with land registration. Better performance of the SVM model compared to the RF model has been demonstrated in this context (Doan, 2022).

3.2. Land value function

Land value refers to the processes of assessing the value of land parcels and properties, as well as the determination of taxation obligations. The valuation is vital for ensuring accurate pricing and stability in the real estate market. Different AI approaches have been used for the valuation process and influential factor analysis, market trend analysis, as well as real estate document analysis. The following sections explain AI-related research within these contexts, with a summary presented in Table 4.

3.2.1. Land and property valuation

3.2.1.1. Expert systems, case-based reasoning, fuzzy logic, and evolutionary algorithms. Initial AI approaches for land and property valuation have used expert systems that are based on rules predefined by experts' knowledge about influential factors on land and property values, such as location and size. Following that, to address the ambiguity and uncertainty inherent in real estate valuation, researchers incorporated fuzzy logic, enabling the integration of linguistic variables and subjective assessments. Using that, imprecise information about land and property values was suitably handled, leading to fuzzy expert systems that allow for consideration of both quantitative and qualitative data within the land and property valuation procedure (Kilić et al., 2019). Moreover, researchers utilised optimisation techniques like GA to fine-tune fuzzy sets and rules for enhancing the accuracy of valuations. On the other hand, regarding to comparative or market approach, case-based reasoning (CBR), which is an algorithm designed for solving new problems by looking at and learning from past cases or examples, has been used for land and property valuation using past sales data (Bonissone and Cheetham, 1997). CBR is especially well-suited for this purpose since it solves new valuation problems by retrieving and adapting to similar previous situations. Considering a new case, similar instances in the past are first found, and the property value is estimated by adapting to the similar cases. Like expert systems, fuzzy logic and GA have been employed for handling uncertainty and facilitating the automation of model parameter tuning, respectively. Emerging artificial neural networks led hybrid models like adaptive neuro-fuzzy inference systems (ANFIS) to leverage the transparency of fuzzy logic to interpret results, and a combination of artificial neural networks and CBR to achieve more accurate estimations (Diwan, 2019). However, these methods may not be effective enough for land and property valuation procedures due to the dynamic and multifaceted nature of real estate markets.

3.2.1.2. Machine learning and deep learning approaches. As computational power grew, machine learning and deep learning offered their capabilities as a robust alternative and transformed rigid and rule-based approaches into flexible and data-driven models which can be strongly capable of continuous learning and adaptation within real estate markets. In fact, leveraging these models through automated valuation models (AVMs) has increasingly enhanced the estimation performance in terms of speed and accuracy compared to traditional methods like the hedonic price model (HPM), which are limited in handling non-linear relationships between value-influencing factors. Initial adoption of learning models involved machine learning techniques for improving model accuracy, and then with the emergence of deep learning techniques, large-scale and high-dimensional data could be effectively processed. Techniques such as decision trees, RF, and GBR have significantly gained the attention of researchers for regression within land and property valuation, aiming at improving accuracy and handling complex and non-linear relationships. To decrease overfitting, RF expands on this by combining several decision trees. This makes it particularly useful in mass appraisal scenarios where datasets could contain noise or inconsistencies. GBR-based models such as XGBoost, LightGBM, and CatBoost improve performance through sequential learning and gradient optimisation, leading to the identification of complex patterns in heterogeneous data. Although no single algorithm is best in every situation, the choice often depends on the characteristics of the dataset used.

However, comparative analysis shows that RF and XGBoost have better performance. Studies indicate that RF can control non-linear interactions and reduce overfitting in mass appraisal compared to conventional linear regression. On the other hand, ensemble methods, including XGBoost, light gradient boosting machine (LightGBM), and categorical boosting (CatBoost), can perform more accurately if diverse datasets are available. Employing machine learning techniques, influencing factors in land and property valuation can be potentially analysed. Research shows that location, property size, and neighbourhood consistently emerge as significant predictors. Concerning this, the integration of these models with GIS has been studied for advancing land and property valuation.

Clustering techniques such as k-means, c-means, DBSCAN, ordering points to identify the clustering structure (OPTICS), and fuzzy adaptive clustering (FAC) are another category of machine learning techniques that have been used for land and property valuation. These techniques are especially helpful for revealing hidden patterns by grouping similar properties based on different features such as location and size. While K-means and c-means divide data into discrete clusters when the number of clusters is known beforehand, DBSCAN and OPTICS excel in

Table 4
Categorized overview of AI-related research in the land value function, with application areas and the objectives of using different AI techniques.

Application area	Focus area	AI model/algorithm/ technique	Description and objective of using AI	Studies
Land and property valuation	Rule-based	CBR	To estimate value based on previous similar cases	(Bonissone and Cheetham, 1997), (Diwan, 2019)
		Fuzzy logic, expert systems, and evolutionary algorithms	To estimate value based on rules defined by experts	(Aurélio Stumpf González and Torres Formoso, 2006), (Król et al.,)(Guan et al., 2008), (Thipayawat et al., 2009), (Kilpatrick and Worzala, 2011), (Kempa et al., 2011), (Kilić et al., 2019), (Surgelas et al., 2021)
	Data-driven	RF and Boosting (GBR, XGBoost, and LGBM)	To estimate value based on historical data	(Yilmazer and Kocaman, 2020), (Carranza et al., 2022), (Gunes, 2023), (Nejad et al., 2017), (Tanamal et al., 2023), (Jamil et al., 2023), (Zaki et al., 2022), (Lasota et al., 2011), (Prasad et al., 2024), (Geetha and Diana, 2023), (Anchaleechamaikorn et al., 2023), (Sharma et al., 2024), (Kaur et al., 2023), (Gandhi et al., 2023), (Ramolete et al.,) (Gnat, 2021), (Almaslukh, 2020), (Ostrikova and Selyutin, 2024), (Su et al., 2021), (Lenaers et al., 2023), (Jafari et al., 2022), (Doumpos et al., 2020), (Gao et al., 2024), (Mete, 2025)
		Decision trees (CART, M5P, rotation forest, dynamic Bayesian tree)		(Nejad et al., 2017), (Jamil et al., 2023), (Prasad et al., 2024), (Geetha and Diana, 2023), (Sharma et al., 2024), (Kaur et al., 2023), (Gandhi et al., 2023), (Ramolete et al.,) (Reyes-Bueno et al., 2018), (Graczyk et al., 2009), (Trawinski et al., 2017), (Lasota et al., 2012), (Lenaers et al., 2023)
		SVM		(Graczyk et al., 2009), (Jafari et al., 2022), (Graczyk et al., 2010)
		Clustering (k-means, BIRCH, DBSCAN, c-means)		(Jamil et al., 2023), (Ramolete et al.,) (Malinowski et al., 2018)
		KNN		(Zaki et al., 2022), (Kaur et al., 2023), (Gnat, 2021), (Jafari et al., 2022)
		ANN		(Yasnitsky et al., 2021), (Abidoye and Chan, 2018a), (Štubšová et al., 2020), (Hoxha, 2023), (Guo et al., 2019), (Torres-Pruñonosa et al., 2022), (Abidoye and Chan, 2018b), (Peng et al., 2021), (Abidoye and Chan, 2017), (Diwan, 2019), (Lee and Park, 2020), (Lin et al., 2021), (Oshodi et al., 2019), (García et al., 2008), (Hamzaoui and Perez, 2011), (Tajani et al., 2015), (McCluskey et al., 2012), (Maselli, 2022), (Foryś, 2022), (Krämer et al., 2023), (Dimopoulos and Bakas, 2019a), (Alexandridis et al., 2019)
		GNN		(Li et al., 2024), (Zhang et al., 2021)
	Comparative	Hybrid	To estimate value based on historical data and compare different methods	(Gao et al., 2022), (Zhao et al., 2019), (Abut et al., 2023), (Krämer et al., 2023), (Naik and Puthran, 2023), (Dimopoulos and Bakas, 2019b)
	Data limitation	KNN, IDW, RF, XGBoost, and LSTM	To generate synthetic land and property samples from limited transaction data	(Jafary et al., 2024)
		VAE		(Lee, 2021)
		ANN, EKF		(Horvath et al., 2021)
	BIM integration	GA-GBR	To estimate value of properties using data from BIM	(Su et al., 2021)
		ANN		(Jafary et al., 2022)
	Data provision and transparency	Decision trees, RF and boosting (GBR, XGBoost, and LGBM)	To estimate value using data from open-source data	(Carranza et al., 2022), (Ramolete et al.,)
		ANN		(Bin et al., 2020), (Gabrielli et al., 2021)
		Fuzzy Logic	To address uncertainties within valuation	(Bovkir and Aydinoglu, 2018)
Influential factor analysis	Impact of urban renewal and energy	ANN	To find how energy classes can influence market prices.	(Maselli, 2022), (Ruggeri et al., 2023)
	Spatial effects	RF	To examine the performance of standalone linear and non-linear prediction models	(Doumpos et al., 2020)
Market trend analysis	Relationship identification	RF and boosting (GBR, XGBoost, and LGBM)	To identify correlations with external factors and fluctuations in different time frames	(Grybauskas et al., 2021), (Mora-Garcia et al., 2022)
		ANN		(Telec et al., 2014), (Telec et al., 2013)
Document analysis	Information extraction and generation	OCR	To extract information from legal real estate certifications	(Hieu et al., 2023)
		ChatGPT	To generate valuation reports and draft contracts	(Cheung, 2024)
Land consolidation	Estimation	Fuzzy logic	To support the negotiation procedures for different stakeholders	(Kilić et al., 2019)
		ANN	To estimate value of land parcels	(Demetriou, 2016)
		GA coupled with game theory	To optimize decision-making for individuals such as landowners to model the complex dynamics of competition, interaction, and cooperation among stakeholders	(Hashemi et al., 2024)

identifying clusters of any shape. This makes them suitable for clustering spatial datasets that have irregular distributions. Fuzzy logic, on the other hand, helps attributes to belong to several clusters with different levels of membership. The importance of effectively handling data heterogeneity and capturing local market trends through clustering techniques has been emphasised by these studies.

By classifying related properties according to characteristics like location, size, land use, and price, these methods are especially helpful for revealing hidden patterns in spatial and attribute data. While DBSCAN and OPTICS are density-based techniques that are excellent at detecting clusters of any shape and managing noise, making them appropriate for spatial datasets with irregular distributions, K-means and c-means are efficient at dividing data into discrete clusters when the number of clusters is known beforehand. Fuzzy logic, which FAC adds to this, enables attributes to belong to several clusters with different levels of membership.

Another widely used technique for land and property valuation is ANNs, potentially capable of modelling complex and non-linear relationships between input variables like location and property and output variables such as property value. The accuracy of this method is dependent on dataset size, data quality, ANN architecture, and input variable selection. Research shows that not careful selection of these factors may result in less or no change in accuracy when compared to traditional multiple regression analysis (MRA). Moreover, the black-box nature of ANNs is recognised as a major issue of using ANNs for land and property valuation, which leads to obscuring how predictions are made. In contrast, MRA models clearly illustrate the relationship between input and output variables and enhance interpretability.

A major challenge in land and property valuation using machine learning and deep learning techniques is the lack of sufficient transaction data for certain property types or location areas, which can cause data sparsity issues. In this regard, complexity analysis techniques have generally been suggested to determine the minimum sample size required for reliable modelling and avoid overfitting, particularly in data-sparse regions. However, researchers have proposed various specific methods. One method is data augmentation using variational autoencoders (VAEs), which can learn from existing data and create new examples that look realistic, particularly suitable for commercial and infrequently traded properties (Lee, 2021). In this method, synthetic land and property samples from limited transaction data are generated to improve the performance of deep learning models. Another method is increasing sample sizes by aggregating data from neighbouring or functionally similar submarkets (Horvath et al., 2021). Spatial imputation methods such as k-nearest neighbours (KNN) and inverse distance weighted (IDW) can moreover be leveraged when missing data in land and property datasets (Jafary et al., 2024). These techniques are, in fact, algorithms that use proximity as the key factor in estimation, making them suitable for heterogeneous but locally consistent data.

Data provision is another issue that machine learning and deep learning techniques have faced for land and property valuation. In fact, both textual and visual data of properties are required for reliable valuation models. Textual data includes basic features such as property attributes (e.g., location, size, and number of rooms) as well as geospatial, environmental, and socio-economic factors. In contrast, visual data includes images of both indoor and outdoor spaces of the properties. Enhancing the capture of this complex information, building information modelling (BIM) (Su et al., 2021; Jafary et al., 2022) and open-source mapping platforms (Carranza et al., 2022) like OpenStreetMap have been proposed by researchers to be integrated into machine learning and deep learning models. BIM can potentially offer both geometric and semantic information about properties, facilitating the data exchange and interoperability using the industry foundation classes (IFC) format that helps different stakeholders work together by sharing data in a standard way. Moreover, employing computer vision techniques like CNNs, visual features from BIM representations can be analysed to make property valuation models more reliable. However, researchers argue that BIM data alone is insufficient and other data like environmental, socio-economic, and legal factors must also be considered, leading to multi-source data fusion. A study has shown that deep neural networks (DNNs) can effectively merge diverse datasets within the property valuation procedure.

3.2.2. Market trend analysis

Gaining insights into the dynamics of the land and property market, particularly during periods of significant change, is an opportunity that machine learning and deep learning can bring to valuation models. Incorporating temporal factors into the models and identifying correlations with external factors have been recognised as critical keys. This often involves splitting the data into different time intervals. In fact, models are trained using data within a defined time window to find out how prices change, and the window is then shifted to adapt to new situations and identify new trends (Telec et al., 2013). For example, the COVID-19 pandemic is such a specific period in which the fluctuations in the land and property market, like reducing prices at the beginning of the period, have been studied using web-scraping and machine learning algorithms (Grybauskas et al., 2021; Mora-Garcia et al., 2022). Overall, better performance of algorithms like RF, XGBoost, LGBM, and CatBoost has been highlighted by researchers.

3.2.3. Real estate document analysis

Leveraging computer vision and NLP techniques has increasingly improved the analysis of documents related to real estate. Automated extraction of information from legal real estate certifications using OCR is recognised as an enhanced solution for filling required fields in the relevant applications (Hieu et al., 2023). Regarding this, texts are first detected through transformer models, which can be customised for specific languages. Templates are then made for answering questions concerning documents by using models like *PhoBERT*. Additionally, applications of LLMs, which are models with a high number of parameters that have been trained on a vast amount of textual data and can understand and generate sentences, have been explored. For instance, the capabilities of the chat generative pre-trained transformer (ChatGPT) have been demonstrated to generate valuation reports and draft contracts, which are time-consuming tasks when conducted by humans (Cheung, 2024). These models are very useful for automating laborious and linguistically demanding jobs, such as creating valuation reports.

3.2.4. Influential factor analysis

A wide range of factors are incorporated into land and property valuation when using data from various data sources through machine learning and deep learning techniques. For instance, the impact of urban renewal and energy class has been investigated by ANNs (Maselli, 2022; Ruggeri et al., 2023). Identifying the most impactful factors provides valuable insights into the behaviour of the valuation model. In fact, employing sensitivity analysis can illustrate how changes in individual factors influence the estimated value of land and property (Dimopoulos and Bakas, 2019b). Property attributes like number of bedrooms, floor area, and garage size, as well as spatial attributes such as proximity to transport hubs and green spaces, are recognised as the key factors influencing the value of land and property. The risk of bias is a major challenge if the models are not properly trained. Nonetheless, this issue can be mitigated using sensitivity analysis to reveal the impact of specific variables and, as a result, improve model transparency.

3.2.5. Land valuation within land consolidation

Traditional approaches for land valuation within the land consolidation procedure depend on manual methods that are conducted by committees. These methods are often slow and costly. One issue in this context is classifying land parcels for the valuation procedure. Researchers proposed fuzzy expert systems to support the negotiation procedures for different stakeholders, aiming at providing a fairer and more accurate land valuation of agricultural land (Kilić et al., 2019). Another study proposed ANNs to be trained based on various land data, such as slope, shape, size, and access, to estimate land values with higher efficiency (Demetriou, 2016). Researchers indicated that integrating these methods with GIS can improve decision-making in this context.

3.3. Land use function

Land use refers to the processes of controlling the usage of land in line with planning policies and regulations. It includes critical activities such as decision and planning support for land suitability evaluation and land distribution, land use planning document analysis, land use classification, and land use change. The following sections explain AI-related research within these contexts, with a summary presented in Table 5.

3.3.1. Land use planning - decision and planning support

3.3.1.1. Land suitability evaluation. Early applications of AI for land use planning have focused on developing expert systems as a decision support tool in which expert knowledge has been encoded as rules, assisting land use planners to evaluate the suitability of land for different uses based on various factors such as slope and proximity to infrastructure. *ILUDSS* (Zhu et al., 1996) and *ALSE* (Elsheikh et al., 2013) are specific examples of these systems in which land suitability for peat cutting and tropical and subtropical crops can be automatically assessed, respectively. On the other hand, to address the uncertainty in quantitative data and normalise the data, fuzzy logic has been employed (Hoang et al., 2022; Ou et al., 2017; Salvacion, 2021). More recently, learning patterns from data and making predictions have been possible by emerging machine learning algorithms, transforming knowledge-based systems to data-driven approaches. Researchers have explored different machine learning algorithms, such as SVM and RF, that have been integrated with GIS and multi-criteria decision-making (MCDM) techniques for more robust land suitability assessments. *FAHP-SVM* and *FAHP-RF*, as an example, have been explored for identifying suitable landfill areas (Mohsin et al., 2022). In addition, SVM-based suitability models are used for different land use planning scenarios, considering a multitude of factors like population density, infrastructure, and environmental vulnerability (Safitri et al., 2020).

3.3.1.2. Land allocation and distribution. One critical task in land use planning procedures is land allocation and distribution, in which the use of different land within an area is determined, aiming at eco-socially and environmentally maximising benefits and minimising negative impacts. This process is, in fact, a multi-objective optimisation problem, which may cause conflicts between objectives. Leveraging AI-driven problem-solving solutions like evolutionary algorithms, such as *UDT-MOEA*, can efficiently address this issue by providing a range of alternative optimal solutions for decision-makers. Moreover, influential factors in land allocation can be analysed by using machine learning and deep learning models. For example, LSTM and MLP have been employed to understand how accessibility to facilities like public transportation impacts mixed land use patterns at the parcel level. These models are very useful to identify the dynamic and non-linear relationships between transportation infrastructure and land use distribution. In fact, DNNs have shown their power to analyse the complex and non-linear relationships between transportation supply and land use.

Beyond the optimisation issue, stakeholder negotiation within the decision-making procedure also needs to be addressed. In this regard, AI offers multi-agent systems (MASs) to simulate stakeholder interactions within group decision-making processes. One study has proposed socially rational agents to learn the social preferences of stakeholders through Bayesian learning, aiming at making more socially acceptable land use decisions. Researchers have utilised agents to represent various stakeholders, each with their own preferences and objectives. The most beneficial advantage of this approach is enabling realistic negotiation and collaboration simulations, leading to equitable outcomes. It has been demonstrated that MAS-based approaches can effectively outperform traditional methods like MCDM in creating agreeable land use plans.

3.3.1.3. Land use planning document analysis. Land use planning documents can be analysed for different purposes using NLP and machine learning techniques. One study has introduced *OPinion mIning from LAND-use planning documents (OPILAND)* to automatically extract opinions from land-use planning documents. In this research, spatial features and organisations within these documents are identified using a combination of NLP and supervised learning. Using lemmatization, morpho-lexical analysis, syntactic analysis, and semantic analysis, named entities are first extracted, distinguishing between places and organisations. As a result, a specialised vocabulary of opinion (SVO) is created, which can incorporate general lexicons of opinions and be contextualised by analysing word proximity and polarity. Considering the frequency and distribution of words within positive and negative document classes, the SVO is then refined, which can lead to the creation of a very specific vocabulary for land-use planning (Kergosien et al., 2014).

3.3.2. Land use mapping and classification

One of the most common areas of study within land use function is the mapping and classification of land use, using different data sources like remote sensing imagery and social network data. AI automates land use/land cover (LULC) classification through advanced machine learning and deep learning techniques, significantly improving accuracy. Several studies have used CNNs to extract features from images and identify different land cover types like urban areas, cropland, forests, and water bodies by learning from labelled training images. Researchers have shown that the effectiveness of these models for land use classification depends on the volume of data as well as the size of the grid cells in images that are used for analysis. However, considering much more data may result in overfitting and a reduction in the performance of CNN-based classification. Moreover, employing smaller cells, which leads to higher accuracy, requires a computational process. Decision trees such as C5 and classification and regression trees (CARTs) are examples of supervised machine learning algorithms used to analyse features extracted from remote sensing data, like LiDAR, and create classification rules (Hermosilla et al., 2010a; Hussain and Chen, 2014; Hermosilla et al., 2010b; Amorós López et al., 2011).

RF, SVM, and DNNs are other algorithms that have been explored widely for land use classification because of their capacity to manage big and varied datasets. While DNNs excel in the classification of water, urban lands, open soils, and high vegetation, these models are not accurate enough for grasslands, bare lands, and agricultural areas. On the other hand, the high effectiveness of RF for classifying agricultural areas has been demonstrated by researchers, especially when combined with multitemporal imagery for crop classification, but it struggles to distinguish high vegetation from agricultural lands. Overall, studies have shown that DNNs can achieve the highest accuracy for classification procedures, followed by RF.

On the other hand, social networks like Twitter and spatial development plans can offer beneficial text data that can be used to classify land uses within an area. In this context, NLP and clustering techniques have been employed to automate the process. In a study, land use information within geo-tagged tweets in the form of keywords, linguistic patterns, and geographical coordinates has been used to be analysed by NLP. As a result, five categories of land use, such as residential, commercial, institutional-governmental, industrial offices, and unbuilt land, have been identified, showing a high accuracy (Aguilar-Ruiz et al., 2022). Providing more up-to-date and cost-effective land use

Table 5
Categorized overview of AI-related research in the land use function, with application areas and the objectives of using different AI techniques.

Application area	Focus area	AI model/algorithm/technique	Description and objective of using AI	Studies
Land use planning	Document analysis	OPILAND (OPinion mIning from LAND-use planning documents) using NLP and SVM	To extract named entities (spatial features and organisations) and their associated opinions from textual documents	(Kergosien et al., 2014)
	Land suitability evaluation	Rule-based system	To assist land use planners as a decision support	(Kushwaha and Oesten, 1995), (Zhu et al., 1996), (Sikder, 2009), (Elsheikh et al., 2013), (Nehme and Simões, 1999)
		Fuzzy logic	To normalize data and address uncertainty in quantitative data	(Hoang et al., 2022), (Ou et al., 2017), (Salvacion, 2021)
		Bayesian network	To integrate different data to evaluate land suitability	(Nehme and Simões, 1999)
		SVM and RF	To build suitability models for different land use scenarios, considering different factors like accessibility	(Mohsin et al., 2022), (Safitri et al., 2020)
		DNNs	To identify high-value land for Green Infrastructure (GI) in urban fringe areas	(Wang et al., 2023)
	Land use allocation and distribution	Answer set programming (ASP) and evolutionary algorithms (e.g., GA)	To generate alternatives and select optimal land use patterns	(Munoz and Everardo, 2016), (Fotakis and Sidiropoulos, 2012), (Karakostas, 2016), (Jin et al., 2008), (Dong et al., 2022)
		Interval constrained cooperative fuzzy (ICCF)	To handle uncertainty in expert evaluations and to determine values for qualitative indices	(Jiang et al., 2023a), (Najafinasab et al., 2015), (Ou et al., 2017)
		GANs	To generate conceptual land use plans based on user-defined parameters, assisting non-professionals in participating in planning	(Park et al., 2023)
		ABM coupled with game theory	To simulate the decision-making process, negotiation, and interactions of multiple stakeholders	(Ghavami et al., 2017), (Behzadi and Alesheikh, 2013), (Wang et al., 2024), (Maleki et al., 2020), (Ghavami et al., 2022), (Abolhasani et al., 2023), (Ghavami et al., 2016), (Abolhasani et al., 2022), (Sadooghi et al., 2022), (Liu et al., 2016)
		Knowledge representation (decision tables)	To represent knowledge and concepts in land use planning; supporting decision-making by linking functional classification theory to planning	(Witlox et al., 2009)
	Impact analysis	LSTM and MLP	To forecast the effect of transportation supply on the MLU pattern at the parcel level	(Almansoub et al., 2022)
Land use mapping and classification	Land use classification - using remote sensing data	CNNs and FCNs	To extract features from remote sensing data and to perform classification on the extracted features and to capture temporal dependencies within the data	(Won et al., 2020), (Perez-Carabaza et al., 2021), (Lv et al., 2023), (Gundermann et al., 2024), (Pavlovic et al., 2022), (Park and Song, 2020), (Moser et al., 2024)
		RF	To classify land use categories	(Vizzari et al., 2024), (Langenkamp and Rienow, 2023), (Hütt et al., 2020), (Akar and Güngör, 2015), (Long et al., 2013), (la Cecilia et al., 2023), (Krivoguz et al., 2023), (Kasahun and Legesse, 2024), (Widyastuti et al., 2024)
		Decision trees (C5 Algorithm)		(Hermosilla et al., 2010a), (Hussain and Chen, 2014), (Hermosilla et al., 2010b), (Amorós López et al., 2011)
		DNNs		(Dianderas et al., 2014), (Amorós López et al., 2011), (Krivoguz et al., 2023), (Kasahun and Legesse, 2024)
		SVM		(Amorós López et al., 2011), (Krivoguz et al., 2023), (La et al., 2014), (Kasahun and Legesse, 2024)
		Clustering (k-means)		(PEÑA ZAMALLOA, 2021), (Eslahi et al., 2024)
	Land use classification - using social network data	NLP and Naive Bayes	To classify textual documents to identify land uses using the contents of Twitter,	(Aguilar-Ruiz et al., 2022)
		ANNs (including GRU), k-means clustering, agglomerative clustering, DBSCAN, TF-IDF, Word2vec	To extract and classify texts of spatial development plans into land use categories	(Kaczmarek et al., 2022)
	Land use classification - using real state data	Clustering (Ward's method, Partitioning Around Medoids (PAM))	To analyse a dataset of buildings to identify building typologies (related to energy retrofitting) according to similarities in their features values	(Martínez-Rocamora et al., 2024)
	Residential land use classification - using housing market dynamics	RF	To classify land uses based on housing market dynamics and identify property types from real estate transaction data	(Raghav et al., 2022)
	Exploring influential factors	SVR, ANN, RF, and GBRT	To identify the most influential factors affecting forest cover	(Yang et al., 2020a)

(continued on next page)

Table 5 (*continued*)

Land use change (spatio-temporal)	Land use classification - using remote sensing data	Decision trees	To classify tree crop change detection	(Gil-Yepes et al., 2016), (Akay and Sertel, 2016)
		LightGBM	To predict land use/land cover and compare with original database	(Řezník et al., 2021)
		RF and SVM	To classify land use categories, and predict land use/cover changes based on analysis of time-series images	(Poortinga et al., 2020), (Binh et al., 2021), (Abdullah et al., 2019), (Fan et al., 2018), (Uhl and Leyk, 2020), (Wahelo et al., 2024)
		ANNs and MLP	To predict land use change under different policy scenarios	(Song et al., 2017), (Gharaibeh et al., 2020)
		LSTM	To project forest cover dynamics and explore influential factors	(Ye et al., 2019)
	Land Use classification using parcel data	RF and ANN	To model binary responses (change/no change in land use status)	(Tepe and Safikhani, 2023)
Urban growth	Urban expansion simulation	CA coupled with CNN and LSTM	To extract potential spatial features from land use maps to address spatial heterogeneity. To learn from time-series data to address the temporal dependency issue	(Huang et al., 2024)
		CA coupled with CNN	To improve CNN-CA model	(Yang et al., 2024)
		CA coupled with decision trees, RF, SVM, KNN, gated recurrent unit (GRU), LSTM	To mine temporal factors and their probabilities in land use change. To capture and learn long-term dependencies in time series data	(Yao et al., 2024)
		CA coupled with non-ordered multinomial logistic regression (MLR)	To model multi-density urban expansion	(Chakraborty et al., 2024)
		CA coupled with ANN	To simulate land use development along metro lines and predict sections at high risk of settlement due to adjacent construction activities	(Gong et al., 2023)
	Identifying urban expansion determinants	RF	To identify the relative importance of different factors driving urban land expansion for different land use types	(Wu et al., 2021)
		MLP	To analyse the spatial determinants of urban expansion and develop scenarios for different spatial planning alternatives.	(Enoguanbhor et al., 2020)
	Growth boundaries optimization	ACO	To determine the optimal urban growth boundaries by maximising urban suitability, farmland preservation, and urban pattern compactness	(Ma et al., 2017)
	Decision-making simulation	ABM coupled with logic scoring of preference (LSP)	To improve the realism of urban growth simulations by capturing the complex reasoning behind agent choices	(Dragićević and Hatch, 2018)
		ABM coupled with game theory	To simulate the behaviour of individual agents (e.g., developers, residents) in the decision-making process	(Kaviari et al., 2019)

information is the prominent point of this study. Researchers have argued that countries that have no digital standard for preparing land use plans may face inconsistencies in land use classifications. In this regard, they proposed methods in which machine learning and NLP techniques have been employed to analyse and automatically classify the textual content of spatial development plans (Kaczmarek et al., 2022). Both unsupervised algorithms, such as k-means, affinity propagation, agglomerative clustering, and DBSCAN, and supervised algorithms such as ANNs, have been experimented with. It has been demonstrated that ANNs can offer promising results, achieving high accuracy in classifying land use types from textual descriptions within heterogeneous spatial plans.

3.3.3. Land use change

Specifically, leveraging the power of machine learning and deep learning algorithms and remote sensing time series data can be applicable for land use and land cover change (LULCC) detection. RF, as an example, has been used for this purpose, in which historical LULC change pattern data have been employed for training the model. Similarly, another study has used LSTM networks to project Australia's forest cover change (Ye et al., 2019). Another prominent application of AI in LULC analysis is the integration of ANNs with cellular automata (CA) and Markov Chain (MC) models. CA is a model with a grid of cells, where each cell changes over time based on simple rules and the state of its neighbouring cells. MC is a model that predicts the future in which the next state only depends on the present state, not on the past. Using these specific models is particularly valuable for simulating and predicting future land use changes. These AI-driven approaches, coupled with platforms like Google Earth engine, are revolutionising LULC monitoring and analysis, enabling more accurate predictions of future land cover changes and supporting sustainable land management strategies. The insights gained from these studies can help policymakers make informed decisions to mitigate the negative impacts of LULC change, such as deforestation and urban sprawl, and promote sustainable development goals.

One specific application in this context is detecting and simulating urban growth. Researchers have shown that both supervised (e.g., SVM) and unsupervised (e.g., k-means clustering) classification methods can be used for detecting changes in built-up land, in which the supervised classification method outperformed the unsupervised method in accuracy. Regarding simulating urban growth, while traditional approaches involve CA, incorporating AI techniques can improve performance in terms of accuracy and efficiency. In fact, the integrated model can leverage the ability of CA to simulate spatial dynamics and the ability of machine learning and deep learning models, such as CNN-LSTM, to learn complex patterns from large datasets (Huang et al., 2024). In addition, deep learning-based urban CA models can be used in feature selection and revealing spatially varying driving forces of urban expansion (Yang et al., 2024). On the other hand, simulating future urban growth scenarios under different planning policies is recognised as another application of AI when combined with other methodologies such as game theory. In fact, ABM has been used to simulate the behaviour of individual agents (e.g., developers and residents), offering a more nuanced understanding of land development decisions and the complex dynamics of competing land uses in rapidly urbanising areas (Kaviari et al., 2019). Moreover, the ant colony optimisation (ACO) algorithm has been studied to determine optimal urban growth boundaries by considering factors like urban suitability, aiming to manage urban expansion and protect ecological areas (Ma et al., 2017).

3.4. Land development function

Land development refers to the processes of designing and constructing new physical infrastructure such as roads and tunnels. It includes activities such as providing building and planning permits, public acquisition of land, land development intensity prediction, as well as detecting illegal buildings. The following sections explain AI-related research within these contexts, with a summary presented in Table 6.

3.4.1. Building permit

The aim of building permits, essential approvals from relevant authorities to start the construction of a new physical building or infrastructure, is to ensure that the construction complies with building codes and other standards and regulations. It is, in fact, a time-consuming process due to lengthy review periods by authorities and the need for significant legwork for the citizens, and requires coordination spanning several departments. AI can efficiently streamline the process, resulting in a reduction of delays. For example, a study has explored the usage of MLP to predict sunlight hours, which is an essential assessment for residential buildings within the permit process (Jiang et al., 2023b). As MLP, a kind of feedforward neural network, excels at learning from complex and non-linear data, it can accurately predict sunshine exposure depending on several variables, including building orientation and position. In addition, considering this assumption that similar users may have similar permit needs, researchers have proposed an online recommendation system to recommend relevant permits for applicants by analysing user similarities using past permit requests and collaborative filtering techniques, aiming at reducing the need for manual consultations (Eirinaki et al., 2018).

The applicability of expert systems to support officers and landowners for checking the land use designation before submitting the permit application is moreover demonstrated (Limsupreeyarat et al., 2017). Most recently, although BIM has offered a digital environment usable for the permit process, translating many rules into this model is still labour-intensive and time-consuming. In this regard, employing NLP techniques has been proposed as a promising solution for the automated computerisation of building regulations (Fuchs, 2023). In addition, NLP techniques can be used to analyse building permit texts for extracting useful information for further purposes, like natural hazard exposure modelling (Schembri and Gentile, 2024).

3.4.2. Construction activities monitoring and illegal buildings detection

Accurate and up-to-date information on the physical extent of buildings is crucial for effective land development. Hence, construction activities need to be monitored, and illegal buildings need to be detected, to ensure adherence to legal standards and zoning compliance. One common approach is employing machine learning and deep learning techniques such as CNNs and RF to analyse remote sensing data for detecting building footprints and effectively distinguishing buildings from other land cover types. Comparing the detected footprints with official cadastral data, undocumented and illegal buildings are identified. For instance, a study has proposed a framework to differentiate between old and new undocumented buildings by analysing temporal changes in height using temporal digital surface models (tDSMs) and FC-DenseNet, which are algorithms designed for breaking an image into meaningful parts (Li et al., 2020). The construction periods and spatial distributions of these structures have been investigated in another similar deep learning-based study, highlighting the disproportionate

Table 6
Categorized overview of AI-related research in the land development function, with application areas and the objectives of using different AI techniques.

Application area	Focus area	AI model/algorithm/technique	Description and objective of using AI	Studies
Building permit	Recommendation	Collaborative filtering	To generate permit recommendations for new users using past permit requests	(Eirinaki et al., 2018)
	Spatial analysis	MLP	To predicts sunlight hour heatmaps on sites with different layouts to optimise the conceptual layout planning of residential neighbourhoods	(Jiang et al., 2023b)
	Compliance checking	Expert system	To determine the permissible land use	(Limsupreeyarat et al., 2017)
	Document analysis	NLP4GED (Natural Language Processing for the Global Exposure Database)	To extract critical exposure information such as building height, construction year, and occupancy from building permit textual documents	(Schembri and Gentile, 2024)
Detection of undocumented or illegal buildings	Undocumented or illegal buildings detection	CBR	To retrieve similar precedent planning application cases, aiding planning officers in decision-making	(Wang and Yeh, 2002)
		CNNs (e.g., FCN, GoogLeNet (Google LeNet), DCNN)	To segment and extract buildings from remote sensing data	(Li et al., 2020), (Li et al., 2022), (Ostankovich and Afanasyev, 2018), (Li and Liu, 2020)
		Feedforward neural network	To identify and classify buildings, automating the identification of unauthorized buildings.	(Osennyaya et al., 2023)
	Building footprint detection	CNNs (e.g., Mask R-CNNs, MS-FCN, MFUN, U-Net, DeepLabV3 + (DeepLab Version 3 Plus), YOLO (You Only Look Once))	To extract buildings from remote sensing data	(Šanca et al., 2021), (Liu et al., 2021), (Shu et al., 2021), (Glinka et al., 2022), (Andaru et al.,)
		RF	To automatically categorize building footprints into different types	(Hecht et al., 2015)
Land acquisition conflicts	Negotiation simulation	Bargaining model ACO	To simulate the negotiation process within the selected candidate areas that have been identified during land acquisition negotiations	(Tang et al., 2020)
		Game theory	To simulates the stakeholder interactions	(Aghmashhadi et al., 2022)
Land development intensity	Prediction of land development	XGBoost, Decision trees, RF, SVM, and GBDT	To predict land development intensity and quantify the importance of independent variables	(Gu et al., 2023), (Yang et al., 2020b)

concentration of undocumented buildings in lower-density regions (Li et al., 2022). Leveraging these techniques has enabled dynamic monitoring of construction progress and identification of illegal buildings by comparing real-time data with approved urban planning data.

3.4.3. Land acquisition

The major issue within land acquisition is the negotiation process between the government and landowners (i.e., farmers). A study has explored the use of the bargaining model to simulate the negotiation process for urban expansion purposes. Factors like land compensation standards, fairness preferences, and discount factors have been considered to determine areas where land acquisition is required. Following that, the urban expansion candidate areas have been simulated using the ACO algorithm. The results show significant increases in farmers' profits compared to standard land compensation, highlighting the model's potential to ensure fairness and reduce land acquisition conflicts (Tang et al., 2020). Other studies have used game theory to simulate the complex interactions between various stakeholders involved in these processes, such as municipalities, developers, and landowners, informing decision-making in the face of competing interests and potential conflicts (Aghmashhadi et al., 2022).

3.4.4. Land development intensity prediction and influential factor analysis

A critical indicator of land development efficiency is predicting its intensity, which can be automated by using machine learning techniques such as XGBoost, RF, SVM, and decision trees. Results of a study show that XGBoost outperformed the other models, handling complex and non-linear relationships between land development intensity and influencing factors, and achieving high accuracy (Gu et al., 2023). In another study, the impact of metro transit on land development has been investigated, resulting in the finding that proximity to metro stations was a significant predictor of development intensity. These data-driven approaches can potentially inform decisions regarding infrastructure developments (Yang et al., 2020b).

4. Conceptual framework and phased road map for intelligent land administration systems (ILASs)

Considering the land management paradigm in which the four core functions are operated holistically, current studies show that AI has been applied to various discrete areas in a fragmented manner, and there is no holistic framework to show how different AI capabilities can be leveraged within LASs. With respect to this, a conceptual framework has been proposed, which is illustrated in Fig. 6. AI techniques can be used in different stages of the data lifecycle to transform the LII part to the intelligent form. Upon intelligent land information infrastructure (ILII), the effectiveness of the data management can be enhanced by using AI capabilities, leading the functions to be operated in an intelligent environment more efficiently and forming intelligent LASs. If issues regarding data, such as fragmentation, can be effectively addressed, decisions can be improved. By consolidating data across different functions, AI enables seamless data integration, ensuring that different LAS functions can access and operate on unified data in an intelligent environment. Moreover, the intelligent infrastructure layer in the framework helps decision-makers to access real-time data in an easier way, which can potentially lead to more timely and informed decisions

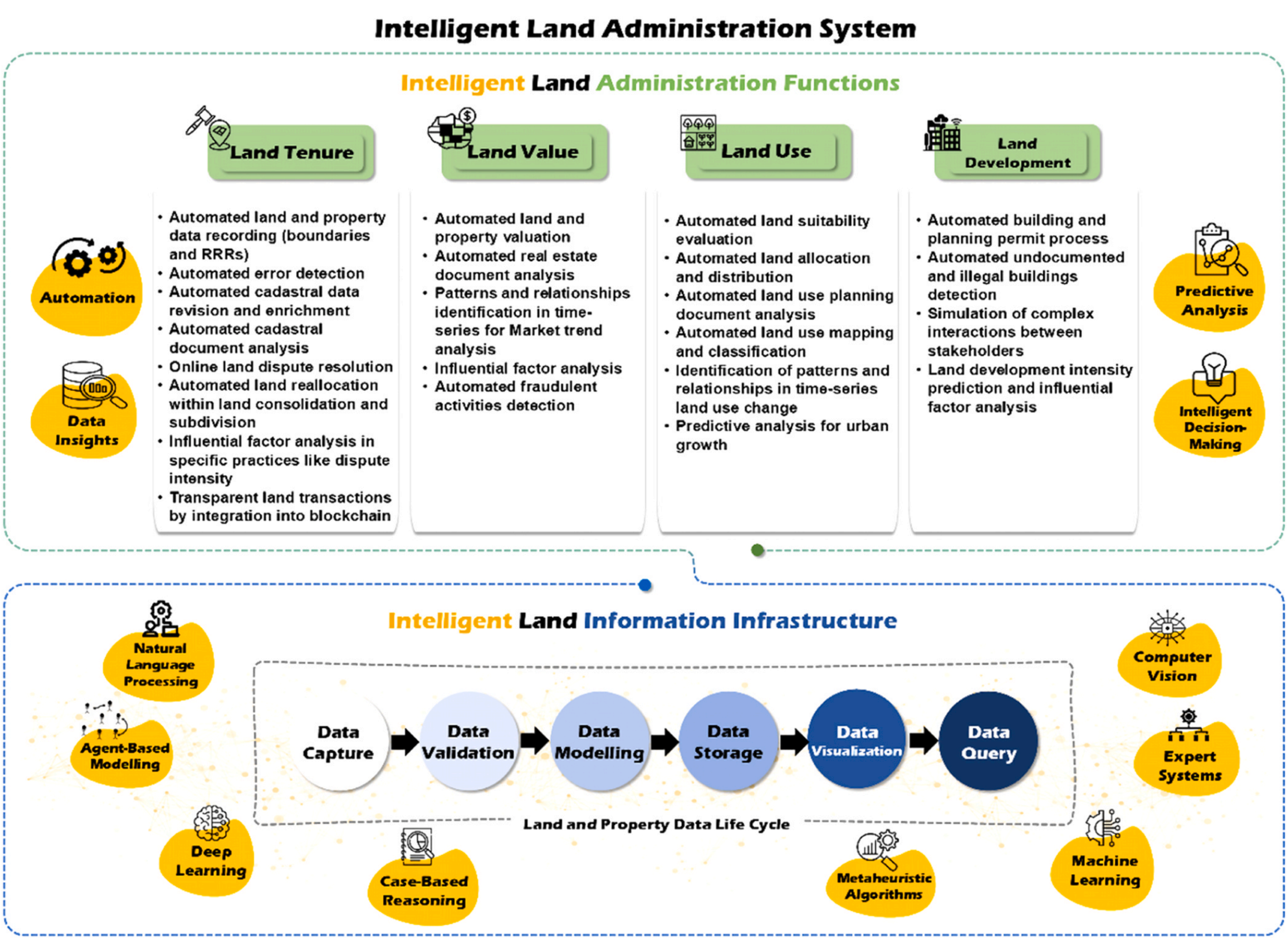

Fig. 6. A conceptual framework for the adoption of AI in the land administration domain.

in the land administration domain. Furthermore, routine tasks can be automated, which can enhance the efficiency of LAS functions. Therefore, the time and resources required for processes such as land transfer, registration, and dispute resolution can be substantially reduced.

To successfully transition from legacy LASs to intelligent ones, clear implementation guidelines are essential. In this regard, a roadmap comprising four interdependent phases, beginning with the establishment of digital infrastructure and progressing to continuous refinement, starting with establishing digital infrastructures to continuous refinement, is proposed, which is depicted in Fig. 7. Each phase is dependent on the successful completion of the previous one to ensure sustainable implementation.

In phase 1, foundational infrastructures for providing a digital environment must be established. It includes deploying appropriate servers with high-performance computing (HPC) and graphics processing units (GPUs) to support the training process, as well as databases for storing digital spatial and non-spatial data. Application programming interfaces (APIs) and web services are also required for data integration across different data providers. Furthermore, legacy land and property data (i.e., cadastral records) must be digitised. In this regard, using OCR technologies for converting paper-based data into digital, structured formats (e.g., LandXML) could be highly beneficial. Additionally, if supervised machine learning models are to be trained in the subsequent phase, labelled data are required, which must be prepared carefully. Adopting standardised data models (e.g., LADM) is also proposed to ensure data consistency and interoperability.

During phases 2 and 3, AI models are developed and deployed, respectively. First, depending on the desired application, models are either trained from scratch or fine-tuned based on prepared datasets to be tailored to downstream tasks like extracting specific information from survey plans. Then, trained models are integrated into current LASs by embedding developed packages into existing platforms. It is critical to make sure that the deployed models are interoperable with other subsystems.

In phase 4, the effectiveness of the deployed models is monitored in terms of speed and reliability. By detecting bugs, the performance of models is incrementally improved over time. As significant new data is available and policies and user needs change, the models should be retrained. In addition to technical performance improvements, security evaluations should also be considered in this phase to protect sensitive land and property data from unauthorised access.

5. Discussion on challenges and future directions

Land administration has consistently required improvement, and because of this, different land reform approaches have been proposed. With the advancement of technology, AI is profoundly reshaping many domains. Nevertheless, to fully harness the potential of AI across the entire land administration landscape, a multitude of research challenges and future directions must still be addressed. The subsequent sections will discuss these relevant issues.

5.1. Technical issues

The development AI models customised for land administration faces technical challenges in terms of data and model design which are discussed in the following subsections.

5.1.1. Data availability and quality

The current trend of studies shows that research within the adoption of AI in the land administration context has shifted from rule-based approaches to data-driven approaches. Although techniques like expert systems can still benefit land administration, emerging machine learning and deep learning models have significantly gained the attention of researchers to provide a flexible environment to learn continually from data and adapt to new situations. Moreover, land and property data is classifiable as big data due to its minute-to-minute production during various processes such as document verification and leasing transactions (Junaid et al., 2024). In this regard, issues related to data must be given special consideration.

Machine learning and deep learning models require large volumes of accurate and up-to-date data to operate well. However, data within land administration in many countries and jurisdictions is either incomplete, outdated, or stored in a fragmented form. Land records are often stored across different agencies, databases, and even physical paper records, which prevents AI from accessing them and learning from them easily and effectively. On the other hand, capturing data from the beginning is a costly and time-consuming process. Moreover, much of the cadastral data has not been digitised and is still preserved in paper form. Hence, regarding 3D land administration, especially in urban areas, these models may face training limitations. If machine learning models are trained on biassed or incomplete datasets, the outcomes may not be accurate. This is particularly problematic in the land administration context, in which decisions impact property rights and land values. Concerning this, one opportunity is applying AI capabilities to accelerate the process of converting the existing cadastral data into 3D digital data models, making them more reusable.

In addition, the quality of the data is also important. The level of complexity in ownership problems is high in cases dealing with land parcels and properties in 3D. The data, especially regarding RRRs, must be free of any error, and any anomaly must be detected. It is essential for the adoption of blockchain technology, which has been proposed to bring security and transparency into the management of land records, property rights, and transactions, ensuring trust and reducing fraud. Once sufficient and high-quality data is available, a benchmark dataset can be made available for developing machine learning and deep learning models.

5.1.2. Model selection, explainability, sustainability, and scalability

The black-box nature of machine learning and deep learning models cannot provide a self-explanatory theory for their results. Although these models are powerful to process and analyse vast amounts of data, they often operate in ways that are not transparent to users. It can

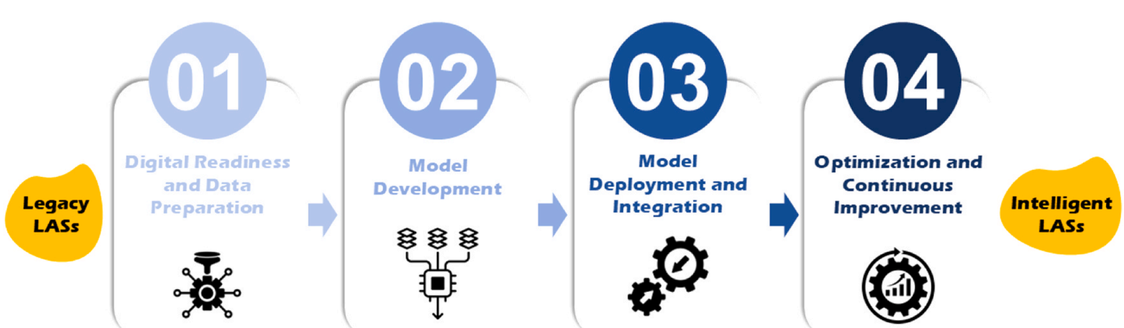

Fig. 7. Phased roadmap for transitioning to intelligent land administration systems (ILASs).

decrease the trust of stakeholders, especially in the land tenure function, which is legally more sensitive and critical. If stakeholders cannot comprehend how the results are generated by a model, they may question the validity of the outcomes. In this regard, it is essential to leverage explainable AI (XAI) within the land administration domain to provide a qualitative understanding of relationships between model features and predictions to help develop more human-understandable AI models. It not only brings confidence for stakeholders but also allows them to find out how different factors, such as the location of a property, contribute to a model's output, such as property value.

In addition, expert knowledge and manual tuning are required to find optimal machine learning and deep learning models. It is a time-consuming procedure, and highly skilled experts are rare for this purpose. Making the procedure more automated can hence be explored to find out how it is possible to develop a model addressing all the concerns on scenario adaptation and comprehensive metrics besides accuracy performance.

The land management paradigm fundamentally seeks to achieve sustainable development. Concerning this, the development of AI models for various purposes within land administration must align with the principles of sustainability. The models must be repeatable to produce consistent results, while data and methods do not change. For example, in property boundary delineation, an AI model used to detect legal boundaries must consistently generate the same boundary lines when using the same survey data. This repeatability is crucial in land administration, in which decisions can have significant impacts on property rights, land use patterns, and environmental conservation. In addition, the models must be expandable to accommodate new datasets, ensuring they are flexible in different circumstances. The landscape of land administration is dynamic, and AI models should be able to integrate this new data without requiring a complete redo. Overall, the misalignment can lead to negative outcomes such as producing inconsistent and unreliable results and failing to adapt to changing situations. Sustainable AI-driven land administration needs to be approached holistically to foster long-term work that can be explored to find the requirements.

Moreover, the scalability of AI models is also important. Different jurisdictions have their own terminologies, rules, and regulations in both surveying and planning processes. For instance, primary parcels vary across the jurisdictions of Australia and New Zealand in terms of number and name, as each government has implemented cadastral systems in a distinct way (Atazadeh et al., 2023). Hence, if AI models are designed to classify parcels across Australia, they must be trained on data representing all jurisdictions. Otherwise, the trained AI model might not be applicable. Without this comprehensive training, the resulting models may lack general applicability and fail to perform accurately in jurisdictions not represented in the training data.

5.2. Legal issues

It is essential to clearly determine accountability in AI models if they unintentionally perpetuate biases and unfairness in decision-making. Unfortunately, it is often challenging to specify individual roles and responsibilities when utilising AI models, as AI failures may be due to multiple reasons, such as biassed training data and errors in programming, or a combination of these. Hence, it is difficult to pinpoint the exact root cause (Novelli et al., 2024). Nevertheless, accountability in AI-driven land administration could be clearer and more enforceable if policymakers establish customised standards and accountability mechanisms like *European Union's AI Act* (Union, 2021).

Another legal issue is ownership rights associated with AI models. Generally, three stakeholders are involved when adopting AI models, including AI model developers who continually train and fine-tune models, AI model owners such as land administration authorities (e.g., government), and AI users that can be land surveyors, land registry officers, local council experts, law experts, urban planners, etc (Battah et al., 2022). However, when AI models are enhanced due to changing requirements, the stakeholders may have concerns about intellectual property and the distribution of benefits generated by new versions of the AI models. Hence, clear frameworks must be established to transparently manage ownership rights associated with AI models using appropriate technologies like blockchain for transferring the model ownership in various circumstances.

Moreover, the outputs of AI models must be validated not only technically but also legally. This is essential that AI models are recognised and accepted legally. Even if outputs could be highly accurate (spatially or non-spatially), a lack of legal validation beyond a technical one can lead stakeholders like land registries to not trust the outputs as official outputs. In this regard, human verification when making the final decision is proposed. Furthermore, it is also important to update regulations in land administration to accommodate the newest AI technologies, in collaboration with technical experts.

5.3. Institutional issues

The implementation of AI technologies can present significant challenges for organisations (Dwivedi et al., 2021), as they often face considerable uncertainty when adopting emerging information technologies (Strauss et al., 2024). This uncertainty is due to various institutional factors. The adoption of AI in land administration adds AI developers as a new stakeholder to the scope of land administration. Thus, organisations require new skills and technical expertise, as well as achieving alignment among diverse actors to have an interdisciplinary perspective. Policy readiness is another critical issue. Existing policies may not be ready to accommodate operational complexities brought by AI. Furthermore, the adoption of AI in LASs requires significant investments in digital infrastructures and staff training, as well as ongoing operational expenses for maintenance. Consequently, shifting from traditional approaches in land administration institutions may lead to reluctance and resistance to adopting AI in current LASs, as the mentioned issues may disrupt institutional norms.

However, if major concerns of professionals are adequately addressed, its adoption can be better, as the success of AI implementation in LASs depends not only on the technology itself but also on land administration professionals' attitudes. Unfamiliarity with new information technology, fears of potential errors, and job displacement are the main concerns in this regard that can be addressed through adequate training, continuous support, and the fostering of an innovation-friendly culture to improve the acceptance of AI in LASs. For example, in Land Tenure Regularisation Program (LTRP) in Rwanda, technology adoption was improved by one-on-one training in each office, as some Land Notaries were unfamiliar with the used software and the hardware (Hughes, 2022).

5.4. Ethical issues

Generally, AI ethics has encountered failures in many cases, with little significant impact on the decisions AI developers make, as AI ethics is often viewed as a secondary concern (Hagendorff, 2020). Although many ethical guidelines have been introduced by different international and national authorities, such as *Artificial Intelligence. Australia's Ethics Framework: A Discussion Paper (*Dawson et al., 2019*)* by the Australian Department of Industry Innovation and Science, and *ITI AI Policy Principles for Enabling Transparency of AI Systems* (Worldwide, 2022) by the Information Technology Industry (ITI) council, it is essential to establish domain-specific ethical guidelines developed by relevant agencies for land administration. This is because certain critical factors, such as validation of training data, that can potentially cause ethical issues like data bias, require deep domain knowledge to ensure fairness and secure trust. The absence of such customised guidelines for land administration is a critical gap that needs a great collaboration of land administration professionals to develop a well-defined framework.

Transparency is recognised as the most important dimension in AI ethics (Jobin et al., 2019). It aims to understand and interpret the rationality of AI models by clearly illustrating how AI models operate and why they produce certain outputs (e.g., decisions) on, for example, sensitive land tenure matters. However, in the context of land administration, not much effort has been made on the transparency of AI models. This is because the main concentration of efforts has been on the development of the model rather than achieving an acceptable accuracy and not making it transparent. So, currently, most of the models are still difficult to interpret for domain experts like surveyors, registrars, and policymakers, and XAI techniques customised for land administration have not been developed sufficiently. However, to mitigate data bias, training data must be carefully collected. It must have a broad and balanced coverage across diverse parts of a specific land administration task, rather than being concentrated on specific parts. Moreover, after training, detecting biases and adjusting outputs to make sure that the model is fair is essential as environments change. Hence, the output must be continuously monitored to maintain equitable performance over time.

Additionally, data privacy and security also need to be considered. Land and property data within land administration are legally sensitive in nature. Personal information of landowners, property boundaries, and the extent of RRRs are all examples of this information within land administration. AI relies heavily on large volumes of data, and hence, privacy and security of the data are essential for maintaining trust and ensuring compliance with legal frameworks. If accessed without proper authorisation or property owners may not be aware that their personal or land-related data is being used for purposes beyond their knowledge or consent, and privacy concerns may arise. In this regard, specific restrictions must be established, for instance, using on-device LLMs like Llama instead of cloud-based ones like ChatGPT, to ensure control over data and reduce the risk of unauthorised access. In addition to privacy concerns, the security of the data is also essential. On the other hand, if security infrastructures are not effective, land and property data could be altered, and the AI algorithms may be exploited, leading to manipulation of outputs. Hence, integrating AI with new technologies such as blockchain is required to trace and verify, for example, land ownership, ensuring that land transactions cannot be tampered with, reducing the risk of fraud.

Equity and dignity are other dimensions of AI ethics, particularly in domains like land administration with diverse stakeholders. Considering the wide range of actors, including land surveyors, registry officers, urban planners, landowners, policymakers, and indigenous communities, it is essential to make sure that each stakeholder has equitable access to AI tools tailored to their roles and needs. Hence, even historically vulnerable communities can benefit from the advantages of AI. Furthermore, human rights must be actively protected. As AI models are increasingly integrated into LASs more and more, the risk of job displacement is likely to rise, particularly among technical individuals. Therefore, inclusive policy frameworks are necessary to mitigate the negative socio-economic impacts on individuals affected by technological shifts.

5.5. Future directions

AI can potentially revolutionise land administration domain by providing more efficient tools. However, some priority areas for future research are outlined in the following subsections.

5.5.1. Natural language for more efficient collaboration and information enquiry

Land administration has a wide range of stakeholders, such as government agencies, private surveyors, land developers, and legal institutions, each of which has its own data formats, standards, and procedures. The diversity of stakeholders leads to challenges in data sharing and querying. Although some solutions have been proposed based on ontology and data integration techniques to provide an interoperable environment, enquiry is still not very efficient. Using natural language, as a common language among the stakeholders, not only enhances efficiency in terms of speed but also eliminates the need to know specialised knowledge about another stakeholder's technical language and standards. Instead of relying on understanding each other's data standards or procedures, stakeholders can use natural language queries to interact with LASs. It can efficiently and effectively eliminate the need to search manually through cadastral databases. NLP techniques can be used for semantic similarities in terms and definitions between data models in land administration (VANĚK et al.,). AI chatbots allow faster communication, greater accessibility, better data integration, streamlined processes, and making it easier for stakeholders to collaborate without needing specialised technical knowledge.

5.5.2. Document reviewing assistant

Various documents are used by different stakeholders within different activities in all land administration functions. Legal documents such as deeds and titles, 2D/3D survey plans such as plans of subdivision and plans of consolidation, valuation reports, tax assessments, land use plans, building permits, and environmental impact assessments (EIA) are all examples of documents that contain physical, legal, and survey information about land parcels and properties. These documents are frequently reviewed by stakeholders for different purposes during the lifecycle of land parcels and properties. For example, subdivision plans are reviewed by land surveyors before any land development to accurately delineate legal boundaries, confirming the extent of RRRs. Each process requires a considerable understanding of the information inside the documents, making it more time-consuming and labour-intensive for accurate decision-making. Developing models based on computer vision and NLP techniques, such as OCR and multimodal large language models (MLLMs), can speed up the review process by automatically recognising and extracting information from unstructured documents and classifying them based on predefined categories. Metadata extraction for organising documents, summarization of lengthy documents for quickly understanding the key information, discrepancy checks for ensuring legal compliance, and error detection, such as missing signatures and depth limitation within the validation procedure, are all applications that can be conducted more quickly by using AI.

5.5.3. Enhanced online dispute resolution

One notable application of AI within land administration is enhancing online dispute resolution (ODR). Resolving disputes by using the judicial system is often time-consuming and requires a long time to reach conclusions. Although AI has been used partially by law experts, using CBR and expert systems as a support system, as well as NLP techniques for communication between parties, these efforts are not able to resolve land and property disputes, which require not only semantic information but also spatial information such as legal boundaries and extension of RRRs, particularly in 3D complex situations where properties may overlap vertically. In this regard, how AI automatically detects legal boundaries and spaces as well as RRRs based on land records, performs advanced 3D spatial analyses to assess overlapping claims and conflicts, and visualises the results to help facilitate discussions among disputing parties can be potentially explored by technical researchers in collaboration with law researchers. Moreover, predictive analysis using historical data about land and property disputes, as well as machine learning and deep learning models, can also be investigated for providing stakeholders with insights into likely outcomes and guiding them towards more informed and fair decisions during negotiation or mediation.

6. Conclusion

The relevant practices within land administration not only need to be automated but must also be more adaptable to new circumstances in response to the dynamic nature of LASs. This can be carried out by gaining from the advancements in AI. Considering the high-level goal of land administration, which is achieving sustainable and resilient development, current AI usage in land administration is still in its infancy, with studies being conducted in isolated contexts. Throughout this review paper, the core functions of land administration have been brought together in the adoption of AI to determine the extent to which AI has been used in each function. Currently, land administration data is often fragmented, incomplete, and stored in non-digitised formats. Key AI techniques such as machine learning and deep learning, computer vision, and NLP have shown significant promise in automating tasks and enhancing the effectiveness of land and property data management for intelligent decision-making. Despite the advantages, the transformation towards fully AI-driven LASs faces significant challenges, such as data availability and legal issues, and for AI to truly reshape land administration, more robust data infrastructures are needed. This research has reviewed the existing literature on technical, legal, institutional, and ethical aspects of adopting AI in LASs and proposed a conceptual framework to guide future developments. It supports policymakers to develop more robust digital infrastructures that are well-prepared to accommodate AI technologies, hence, having more responsive and data-driven LASs.

Overall, regulatory frameworks governing AI usage in land administration are still in their infancy, and the lack of comprehensive legal frameworks in this context is apparent in many countries and jurisdictions. Hence, it is essential to establish legal and institutional policies when applying AI in land administration by governments in which the roles and responsibilities in various circumstances are clearly defined. Moreover, collaboration among researchers, practitioners, and policymakers in the land administration domain is a key point. Working together can facilitate achieving more sustainable and resilient AI development and deployment, making sure that the developed models can truly make LASs intelligent. Integrating AI-driven LASs with other technologies such as blockchain and augmented/virtual reality (AR/VR) presents significant opportunities that can bring advantages in terms of transparency and user engagement.

CRediT authorship contribution statement

Hamid Hosseini: Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Behnam Atazadeh:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Abbas Rajabifard:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Behnam Atazadeh reports financial support was provided by Australian Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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