

Immersive analytics meets artificial intelligence: A systematic review

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Abstract Integrating artificial intelligence (AI) with immersive analytics (IA) represents a promising means of leveraging advanced computational techniques to enhance data visualization and analysis. This study examines the state-of-the-art of AI-IA integration by addressing three key research issues: the significant application domains, the AI techniques used and their combinations, and current challenges and future directions. Results of reviewing 43 relevant studies reveal that AI-IA integration is still in its early stages, as existing research has mainly focused on a limited range of data types and application scenarios. By analyzing the application domains, this systematic literature review supports previous findings of important applications in the fields of education, manufacturing, and healthcare. At the same time, it identifies emerging applications that have progressed from XR and AI domains to AI-IA integration, such as sports events, assistive systems, urban planning, and disaster management. We contribute to extending established visual analytics (VA) pipelines into XR environments with integrated AI techniques. AI techniques are identified as contributing in five ways to this IA pipeline. Our contribution also includes identifying four key challenges and seven opportunities for future exploration. The review concludes that combining AI and IA holds the potential to create innovative applications using advanced AI and immersive visualization techniques. We present an overview of these applications and address key issues for future development.

Keywords immersive analytics (IA); artificial intelligence (AI); visual analytics (VA); visualization; virtual reality (VR); augmented reality (AR)

1 Introduction

Emerging technologies, especially artificial intelligence (AI) and extended realities (XR), have shown unrivaled promise for real-life scenarios such as healthcare, education, and interdisciplinary research areas such as intelligent analytics for large data. Immersive analytics (IA) is a recently developed domain that extends conventional visualization and visual analytics (VA) into XR spaces. It integrates data visualization in immersive environments such as virtual reality (VR), augmented reality (AR), or mixed reality (MR) to help find data patterns, to support inference, reasoning, and decision-making.

Via various research attempts to address the importance of data visualization in immersive environments, IA inherits and extends features from traditional VA, mainly based on machine intelligence and monitor-based displays. Dating back to 2015, a foundational definition of IA was proposed: an approach that conducts data analytics in immersive environments for seamless workflows [1]. In advanced visual spaces of three dimensions (3D), IA enables collaborations between humans and visualization, and between multiple users. Not only typical immersive technologies (VR, AR, and MR) can contribute to building IA systems that allow collaborative efforts, but other visualization tools such as interactive whiteboards, mobile communication devices, and sensor devices are also involved. Following this concept, IA is further positioned to use engaging, embodied analysis tools

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to enhance data understanding or to support decision-making [2]. It removes barriers between humans and displays by enabling natural interaction and multi-modal data presentation. As interaction techniques and visualization methods are typical research focuses in VA, and research efforts in the past decade have extended them into the IA domain, the boundary between VA and IA has remained unclear due to their shared data analytics workflows.

Recent breakthroughs in the IA community surpass traditional VA, such as collaborative analytics, spatial immersion, and multi-sensory presentation [2]. Kraus et al. [3] have highlighted four guiding scenarios in which immersive visualizations may add significant value, including situated analysis based on AR, spatial data and spatial tasks, collaborative tasks, and data presentation with engagement. However, there are still challenges in spatially presenting data, best practices of interaction, understanding human perception, and ethical issues [4]. Therefore, it is still too early to conclude that IA with these integrated technologies is an advance over long-standing traditional VA.

As AI has been the leading force in complex data analysis in recent years, it is reasonable to hypothesize that combining XR's advanced visualization capability and AI's computing capability could provide cutting-edge features for IA. Therefore, this work aims to present a systematic literature review of the research into AI-IA combinations and provide insight into future directions. Therefore, a relatively narrow focus is considered, as shown in Fig. 1. Specifically, we intend to answer the following research questions (RQs):

- (1) *RQ1*: What are the main application areas in which IA has been applied in combination with AI techniques?
- (2) *RQ2*: In a general IA pipeline, what range and types of AI techniques have been utilized to advance IA solutions?
- (3) *RQ3*: In studies integrating AI techniques with IA, what are the opportunities and challenges that can be identified from the research landscape and technical perspectives?

By answering the three research questions, this review contributes in two ways: (1) it outlines the research landscape of the combination of AI with IA, and (2) it identifies future directions for utilizing AI in the IA domain.

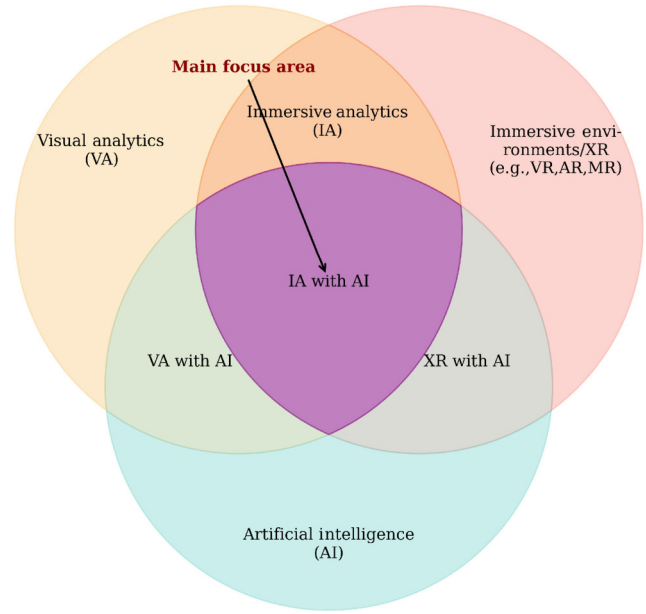


Fig. 1 Position of IA with AI. The central focus is grounded in AI, XR, and conventional VA.

2 Related work

The research focus of this systematic literature review lies at the intersection of IA and AI, while posing an emphasis on IA perspectives. AI-IA integration has deep roots in the intersecting areas, including AI, VA, and XR, as illustrated in Fig. 1. Therefore, related surveys, reviews, and similar relevant work can be categorized into two main areas: those related to IA and those exploring AI within the context of VA.

2.1 Previous reviews of IA

Recent surveys of IA have identified many design challenges in the IA community [4–7]. Skarbez et al. [5] positioned IA as “*the science of analytical reasoning*” that features an immersive experience over and above that provided by conventional displays and high-level human-computer interaction. The highlight of the extra immersive experience entailed IA as an emerging domain that presents visual components and involves users in XR environments. Specifically, they identified integrating machine learning (ML) technologies into IA as one of the technical challenges with system compatibility issues. However, there is still very little discussion of integrating AI with IA.

A notable number of studies have focused on the design space of IA systems, including discussions on critical aspects such as visualization, interaction,

multi-user collaboration, and evaluation [4]. From a theoretical perceptual psychology viewpoint, Moloney et al. [8] proposed a novel framework for presenting high-dimensional data in VR with multi-sensory representations. Despite the lack of practical applications, they regarded IA as a significantly different domain from traditional VA, as the egocentric visualization mode allows multi-sensory presentation of objects in immersive environments. From a user-centered design perspective, Panda et al. [9] investigated the relationship between design perspectives and the user's purposes of immersive visualization. This work identified abstract data representations as beneficial to visual manipulation, while concrete representations can lead to better semantic understanding for analysts. Sardana et al. [10] focused on the design methodology of IA and proposed an iterative design framework for IA systems. Through an empirical study, they compared the impact of the two primary frames of reference for immersive visualization: *egocentric* (human-centered) and *exocentric* (visualization-centered). More recently, Saffo et al. [11] reviewed studies in the recent ten years to identify the primary dimensions for the design space of IA systems. From immersive technologies and data types to visualization techniques, they provided a taxonomy of the IA design space and guidance for future exploration.

There have also been reviews investigating visualization techniques [12] and interaction methods [13] with specific data targets and tasks. For example, Kraus et al. [12] surveyed relevant studies from 1994 to 2020 and analyzed the state-of-the-art of visualization techniques for abstract 3D data in IA. For collaborative understanding tasks, VR environments were found to be more conducive to user conversations and interactions and equal contributions than traditional desktop displays [14]. Serrano et al. [15] continued to focus on spatial interaction in IA for understanding. The existing survey concluded that multi-sensory interaction in IA was not sufficiently explored, and further investigation of best practices and real-life applications were identified as promising directions [6]. Dai et al. [16] proposed novel methods enabling precise remote interaction with distant objects in VR, with a view to optimizing interaction solutions in IA. Jamaludin et al. [17] systematically reported application scenarios for IA and methods of evaluation of IA systems.

Their work identified six application scenarios of IA systems, including geographic information systems (GIS), healthcare, engineering, computer science, architecture, and astronomy. They also identified three main evaluation methods: use case demonstration, property measurement, and comparative study. They presented an overview of IA application scenarios and mainstream evaluation methods while leaving the technical synthesis for future work.

2.2 Previous reviews of VA with AI

Prior research has investigated advances in combining AI with VA for interpreting complex AI models or improving the performance of VA systems. At a theoretical level, research directions have explored the combination of AI and VA for decades, especially for application domains with complex data analytical tasks such as geography and cyberspace [18].

Based on the knowledge generation model of VA proposed by Sacha et al. [19], combinations of AI and VA can be categorized as either using AI to assist visualization (AI4VIS) in the data analytical process or using visualization to enhance the transparency of AI (VIS4AI) [20]. AI and visualization are integrated and can benefit from each other in data analysis systems. Although this study summarized numerous existing studies in this area, the findings indicated that integrating AI and VA required further exploration. Simultaneously, Nazemi [21] analyzed the benefit of VA to enhance explainable AI (XAI) and using AI to support knowledge extraction in VA, which again represented VIS4AI and AI4VIS. Moreover, they took one step further by proposing a VA model with a human-in-the-loop [22] in AI. Specifically, by combining visualization with natural language processing (NLP) methods, they tried to integrate human intelligence in providing feedback and decision-making with the machine intelligence of AI for complex decision-making processes. A recent survey identified key challenges and opportunities in integrating foundation models for visualization [23], where advanced AI techniques were identified to support tasks in visualization pipelines (FM4VIS). At the same time, visualization can also support the explainability of foundation models (VIS4FM).

While prior studies have indicated that the IA community and research community combining AI and VA are on two separate tracks, the analytical



workflow of VA can be adapted by IA. Additionally, the combination of AI and XR has emerged as a powerful tool for conferring intelligence on XR and interpreting XR-generated data. Applications have been investigated across various domains such as education and training, medical diagnosis, gaming applications, and advanced visualization [24]. Most of these applications have combined the computing power of AI and the convenience of XR for presenting data and environments. Therefore, advances in AI techniques applied to VA could potentially benefit IA by providing more robust data processing and predictive capabilities. However, gaps remain in the direct application of AI with IA. To the best of our knowledge, this study is the first to examine the methodological details of combining AI with IA and application scenarios. We aim to identify the challenges of combining AI with IA and provide an overview of possible opportunities.

3 Method

To answer the proposed research questions, this systematic literature review is conducted following the guidance of the *preferred reporting items for systematic reviews* (PRISMA) statements [25]. Specifically, we collected a series of primary studies involving AI and immersive VA tasks. The inclusion of target studies followed strict criteria as this systematic literature review investigates the research trend at the intersection of three emerging domains: AI, IA, and XR.

3.1 Search strategy

Our search strategy included using web search engines provided by digital libraries. Four database libraries were used to collect relevant studies: Scopus (<https://www.scopus.com/>), Web of Science (<https://www.webofscience.com>), IEEE Xplore (<https://ieeexplore.ieee.org>), and the ACM Digital Library (<https://dl.acm.org/>), which contain studies from most mainstream venues. We conducted a topic-based search using the four search engines to gather related studies with matching terms in titles, abstracts, and author keywords. The search process was divided into a pre-search and a formal search. The pre-search was carried out to investigate the validity of topics using the keywords *immersive analytics* and *AI* in Scopus. Then, a formal search collected relevant studies with

an expanded search string. To ensure that all relevant studies were included, we did not restrict the year of publication or subject areas classified by search engines.

3.1.1 Search string

Two critical factors influence the formation of the search string. First, since IA has only recently emerged and various synonyms have been adopted within this research community, defining the boundaries of this research area can be challenging. We adopted existing definitions [1, 2] and extended them to a more general one: *a research focus on leveraging advances in immersive data analytics to support the decision-making process*. This suggests potential overlaps between data analytics and immersive technologies. Additionally, in AI, sub-field-specific thesauri are frequently used, which causes the simple combination of the two keywords to yield a limited number of studies. Phrase searches with loose proximity (e.g., *analytics AND visual**) can provide a more comprehensive search. Therefore, the search string was formulated as a combination of three search blocks using *AND* operators, which target three critical contextual requirements for the collected studies: IA or data analytics, AI, and immersive environments. Immersive environments serve as supplementary elements for data analysis studies without explicit immersive terms. The search string represents them by terms such as “virtual reality”, “augmented reality”, and “3D visualization space”.

The search string was structured as shown in Table 1. *OR* operators connect all related synonyms

Table 1 Search string. The three search blocks are defined given the synonyms of immersive analytics-related keywords (*IA-related*), AI-related keywords (*AI-related*), and immersive environment-related keywords (*IE-related*)

Search block	Sub-string composition
IA-related	“immersive analytics” OR “visual analytics” OR (“analytics” AND “visual*”) OR (“predictive analy*” AND “visual*”)
AI-related	“artificial intelligence” OR “AI” OR “machine learning” OR “ML” OR “deep learning” OR “DL” OR “reinforcement learning” OR “RL” OR “computer vision” OR “CV” OR “neural network” OR “NN” OR “natural language processing” OR “NLP”
IE-related	“immers*” OR “virtual reality” OR “augmented reality” OR “VR” OR “AR” OR “extended reality” OR “XR” OR “mixed reality”

in the three search blocks. In the *IA-related* group, we included phrases “immersive analytics”, “visual analytics”, any “analytics” appearing together with “visual”, and specifically “predictive analyze (-sis/st)” appearing together with “visual”, as closely related expressions. For the *AI-related* group, AI is regarded as a general domain, including all state-of-the-art algorithmic techniques and sub-domain applications. Thus, the search string included typical AI sub-domain keywords such as “machine learning”, “deep learning”, “reinforcement learning”, and their abbreviations. In addition, we added the immersive environment as a separate group to help identify studies that may not explicitly contain “immersive analytics” in the text but have conducted analytics in an immersive environment (VR, AR, MR, and XR). Identifying the relevance of such content at the initial phase is challenging, but it may contain valuable information in this field. Adding this search block did not introduce subjective bias since immersive environments are involved in IA by definition.

3.1.2 Search procedure

The search procedure followed an iterative approach, starting from an initial search string that targeted the most relevant studies. As terminology in IA is often not standardized and relevant studies in AI are abundant, broad search keywords can introduce many irrelevant studies. Additionally, starting a search with a simple search string may help validate the

research area at the initial stage. Therefore, the search string was expanded iteratively to detect the optimal combinations of terms in Scopus. In Scopus, three filters were applied throughout the search process to ensure the quality of the retrieved studies. First, we included English-language publications. Also, we excluded publication type *errata* because the original publications should have been included in the literature, and corrections can often be retrieved in their references. We also excluded conference reviews with no full text or authors, containing only abstract information. Once a final search string was formulated for Scopus, we transferred the search to the other literature search engines.

3.2 Evidence selection

The search query finally returned 345 studies from the four search engines. After removing duplicates, we formed a collection of 272 qualified studies. The evidence selection process consisted of two phases, with all authors collaborating to minimize potential subjective bias. The first phase included assessing relevance based on the titles, abstracts, and keywords for each study and evaluating accessibility, while the second phase assessed each study according to its full text.

We established five exclusion criteria (EC) and three inclusion criteria (IC), outlined in Table 2, to identify studies that were not aligned with our focus. Studies that were not written in English were excluded during the search process. As we did not set

Table 2 Exclusion criteria (EC) and inclusion criteria (IC) for study selection

Exclusion criteria	Description
(EC1) <i>Has missing terms</i>	IA or its synonyms were not mentioned, although some studies focused on the combination of AI and XR, or studies focused on IA lack the connection to AI.
(EC2) <i>Keywords used as examples or background</i>	Keywords such as AI, IA, and XR were used for describing the research background or examples for other issues.
(EC3) <i>Not full-text</i>	Conference reviews gathered from Scopus, errata, and conference proceedings were considered not full text and excluded.
(EC4) <i>Irrelevant topics</i>	Some keywords matched but were used for addressing another research focus. Abbreviations of keywords appeared with different meanings (e.g., MR for medical representative or mitral regurgitation).
(EC5) <i>Survey, review or position paper</i>	Surveys, reviews, and position papers that contributed mainly to theoretical synthesis were excluded: this review is only to use primary studies.
Inclusion criteria	Description
(IC1) <i>Application focused with AI and IA used in method</i>	Studies that focus on applications but contain immersive analytics in methods with AI techniques used should be included.
(IC2) <i>AI technologies contained in the method for IA</i>	Studies that present data analytics in any immersive environment with the sub-field of AI technologies should be included.
(IC3) <i>Ethical focus</i>	Studies that discuss ethical issues of immersive technologies or AI technologies should be included.



any constraints on publication language in evidence selection, and the automatic exclusion of conference reviews or erratum reports is only available in Scopus, studies from the other three search engines could still include such outputs; these were manually excluded. In the first screening phase, we checked whether the required search terms were missing from the title, abstract, and keywords of each paper. Furthermore, studies were excluded if the search terms appeared in the background description or were used as examples in the abstracts of included studies. At this stage, we excluded 85 studies. In the second screening phase, we required the full text for each paper and conducted a more thorough investigation of the content to assess whether to include each paper. We also excluded secondary studies such as surveys, reviews, and position papers. This phase excluded 148 records from the previous corpus.

A snowballing process was then conducted based on reference crawling and citation chaining from the 39 included studies and key venues to form a more comprehensive corpus. A final corpus of 43 studies was formed, with 4 additional papers included from snowballing. The flow chart of the filtering and screening processes is presented in Fig. 2.

3.3 Data extraction

Information offering key insights into the research

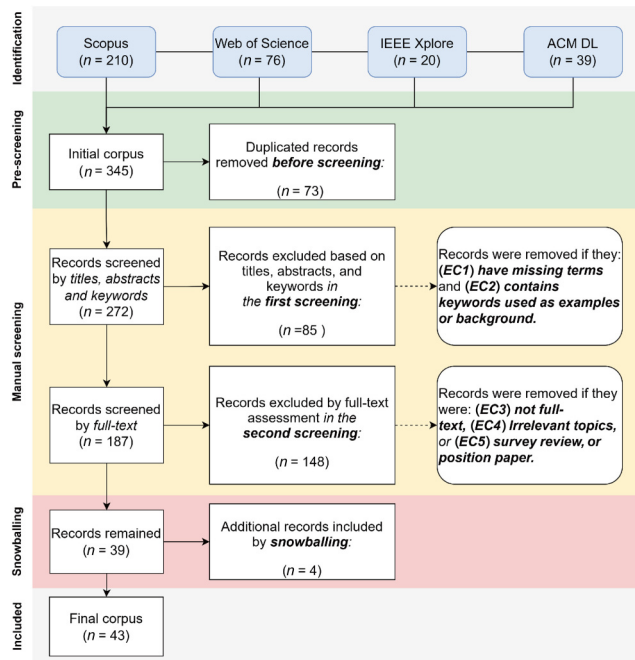


Fig. 2 Flowchart of the selection process from identification of sources to the final collection of studies, forming a corpus of 43 papers.

questions was extracted and synthesized based on the corpus. This data extraction process unified key factors across different study formats, including study types, visualization technologies, display devices, application domains, and technical aspects. A preliminary extraction of research topics was conducted to present an overview of the corpus: see Section 4. Besides, application domains involved in the corpus were categorized and analyzed for answering **RQ1** in Section 5. For **RQ2**, the data extraction centered on technical aspects and tasks in the AI domain, mapped into an IA workflow; findings are presented in Section 6. Furthermore, we analyzed different research contributions, such as proposing novel methods and application domains or focusing on theoretical perspectives and architectures. A comprehensive synthesis of current research landscapes and future directions was conducted based on the data extraction and is provided in Section 7 to answer **RQ3**, which involves an overview of research topics, technical constraints, and potential future directions.

4 Overview

This overview starts with a quantitative analysis of publication outlets (venues) for the 43 papers. As papers in the corpus are from conference proceedings, journals, workshops, and books, we extracted the source information of each paper and encoded them into these four publication types. An overview of publication outlets is presented in Fig. 3; abbreviated outlet names are provided in full in the Appendix. These results show a wide range of 32 publication outlets. The primary type is conference proceedings (18/32), followed by journals (11/32), workshops (2/32), and book chapters (1/32). Furthermore, conference proceedings on XR, AI&XR, and interactive visualization interfaces are the primary publication venues, such as the *IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR)*, the *IEEE International Conference on Artificial Intelligence and Virtual Reality (IEEE AIVR)*, and the *IEEE Transactions on Visualization and Computer Graphics (IEEE TVCG)*. The journal *Applied Sciences (Switzerland)* and conference proceedings of the *CHI Conference on Human Factors in Computing Systems (ACM CHI)*, the *ACM International Conference on Interactive*

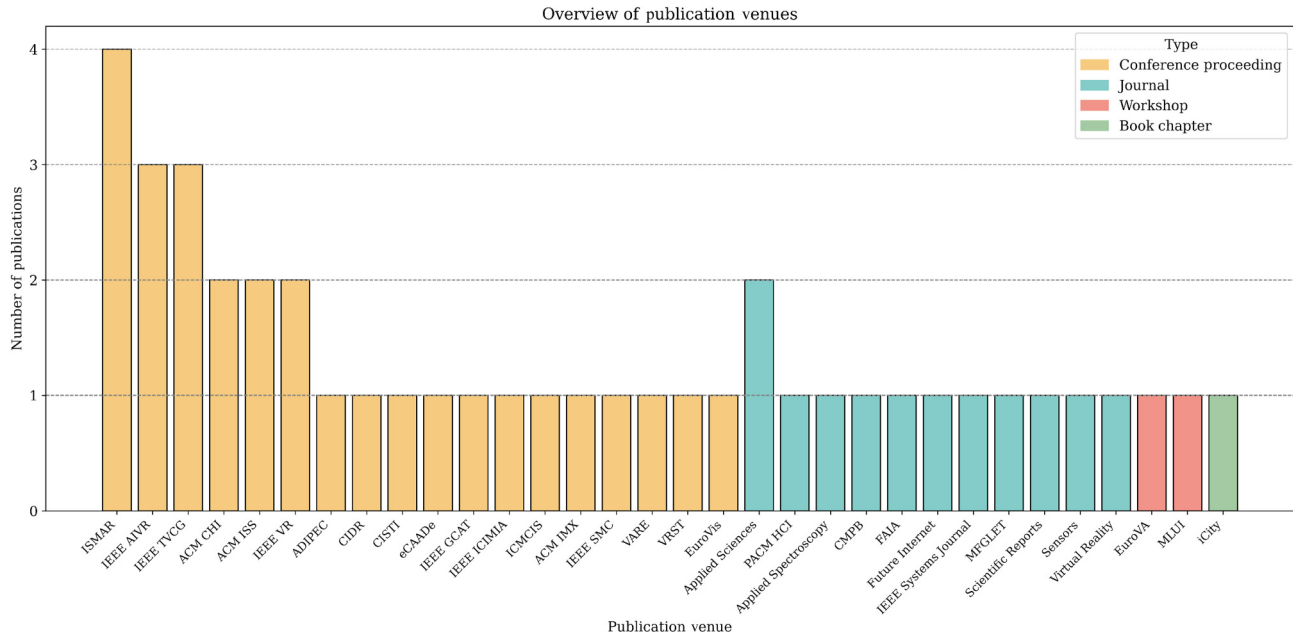


Fig. 3 Distribution of publication outlets for included studies. Publication outlets are abbreviated for layout purposes; full outlet names are provided in the Appendix.

Surfaces and Spaces (ACM ISS), and the *IEEE Conference on Virtual Reality and 3D User Interfaces* (IEEE VR) are also noticeable publication outlets for relevant papers.

To address the current research trends of the intersection of AI and IA, an analysis of publication information for the 43 included studies was conducted, based on five aspects: (i) publication year, (ii) study type, (iii) visualization technology, (iv) display devices, and (v) whether it concerned a specific application domain. Without limiting publication years, we found that publication years of the included studies varied from 2017 to 2024. The study type refers to the different research focuses of the studies: theoretical studies, technical or implementation studies, and empirical studies by the IA research community. As surveys and review papers were excluded by the selection process, no reviews or survey studies were categorized here, but are summarized in the related work. Visualization technologies are categorized into VR, AR, and MR. We categorized existing display devices used for immersive visualization into HMDs and mobile devices. In addition, an *unstated* category was used to group the studies without specific target devices. Although large-screen setups are usually considered display devices in the realm of XR, no included study involved large-screen devices as the target display.

Thus, we ignore this display type in the overview.

Table 3 overviews all included studies. An increasing publication trend can be identified over recent years. Most included studies focused on a single study type. Technical studies were identified as the primary study type: most studies focus on proposing novel frameworks, application strategies, or implementation of systems. Only two papers focus primarily on theoretical issues [30, 31]. Empirical studies were identified as the second primary study type. VR and AR are the two main visualization technologies among the four identified types. The results also show that most IA implementation targeted HMDs, followed by mobile devices.

5 Applications

The included papers are categorized into application areas in general domains such as education, healthcare, and manufacturing. Based on the corpus, the analysis identified eight application domains: education and training, manufacturing, smart healthcare, urban planning, assistive systems, disaster management, sports events, and military communications. However, as some studies contain no application in specific disciplines but rather focus on the technical perspectives of AI or IA systems, we propose an implicit *research domain* category to

Table 3 Overview of the 43 included studies organized by publication year (number of studies in each year given in parentheses), study type, visualization technology (VR, AR, MR), display devices (HMDs, mobile, unstated), and whether application domains are included (✓ for yes). Color-coding with transparency is applied to represent partially marked features. P and S with lower and higher transparency indicate the *primary* and *secondary* study types identified in a paper

Paper	Year (#)	Study type			Visualization technology			Display device			With applications
		Theoretical	Technical	Empirical	VR	AR	MR	HMD	Mobile	Unstated	
[26]	2024 (3)										✓
[27]											
[28]											
[29]	2023 (9)										✓
[30]											✓
[31]											
[32]											✓
[33]											✓
[34]											✓
[35]											
[36]											
[37]											✓
[38]	2022 (8)										
[39]											✓
[40]											✓
[41]											✓
[42]											
[43]											
[44]											✓
[45]											
[46]	2021 (8)										✓
[47]											
[48]											✓
[49]											✓
[50]											✓
[51]											✓
[52]			P	S							
[53]			P	S							✓
[54]	2020 (6)		P	S							
[55]											✓
[56]		P	S								✓
[57]											✓
[58]											✓
[59]			P	S							
[60]	2019 (5)										
[61]			P	S							✓
[62]			S	P							
[63]											✓
[64]											
[65]	2018 (3)										✓
[66]											✓
[67]			P	S							
[68]	2017 (1)										

identify such studies. After the analysis in Table 3, 18 papers were classified into two main research

directions: the (*R1*) *IA domain*, and the (*R2*) *AI domain*. We encoded the identified applications

(A1–A8) and research domains (R1–R2) in Table 4, which are presented with descriptions and significant sub-domains, numbers of mapped studies, and detailed references.

5.1 Education/training (A1)

The technical advances of AI and XR have enabled real-time, interactive visualization with intelligent learning systems in education and training scenarios. Research on AI-supported IA has contributed to education and training by enabling engaged learning experiences and intelligent platforms for collaboration and learning analytics. Two primary directions are identified with four papers focusing on education and training: (i) interactive visualization of educational

contexts and (ii) IA platforms for collaborative learning.

5.1.1 Interactive visualization of educational contexts

One major research focus involves developing methods to interactively present complex and often non-intuitive learning elements for educational purposes. These methods aim to address challenges in understanding abstract or opaque concepts, such as deep learning (DL) models or ensemble methods in AI education, where intermediate decision-making processes are difficult to interpret. For example, Meissler et al. [63] introduced a VR-based visualization of convolutional neural networks (CNNs) using 3D representations to illustrate model

Table 4 Application domains identified from the corpus of the 43 included studies. The identified applications are categorized into eight professional disciplines (A1–A8) and two research domains (R1–R2). Descriptions of each category represent the specific application scenarios or purposes of AI–IA integrated systems. Sub-domains are presented when necessary to group mapped references with similar application perspectives

Category	Description (with sub-domains)	Count	Reference
(A1) Education/training	Enhancing learning with interactive visualization and intelligent tools for complex educational content	4	
	- Interactive visualization of educational contexts	3	[49, 58, 63]
	- IA platforms for collaborative learning	1	[32]
(A2) Manufacturing	Improving manufacturing workflows through immersive tools for defect detection, process monitoring, and maintenance	6	
	- Process inspection	3	[33, 50, 61]
	- Manufacturing environment inspection	2	[44, 51]
	- Machine maintenance	1	[55]
(A3) Smart healthcare	Enhancing patient care with data-driven insights and IA tools for managing multi-source healthcare data	5	
	- Frameworks and techniques for IA of patient data	4	[30, 39, 48, 65]
	- Data collection from multiple sources for city-scale healthcare networks	1	[29]
(A4) Urban planning	Using IA to visualize and analyze geospatial and meteorological data for urban design and planning	2	[41, 56]
(A5) Assistive systems	AR-based assistive systems for task guidance	2	[34, 66]
(A6) Disaster management	IA of geospatial data or social network data for natural disaster management	2	[46, 57]
(A7) Sports events	IA for analyzing sports events for gaining performance insights and promoting audience engagement	3	[26, 37, 40]
(A8) Military communication	Exploring data in XR to enhance remote data communication and tactical decision-making in crisis areas	1	[53]
(R1) IA domain	Research on defining, evaluating, and collaborating in IA systems for general and specific tasks	13	
	- Design perspectives of IA systems	7	[28, 38, 42, 43, 47, 67, 68]
	- Collaborative IA	2	[27, 45]
	- Situated analytics in IA	2	[36, 64]
	- User behavior analysis for IA	2	[31, 62]
(R2) AI domain	Research on IA for visualizing AI models and analysis and model-training processes	5	
	- Interactive visualization of AI models	3	[52, 54, 60]
	- AI-human collaboration in interactive ML training process	2	[35, 59]

architectures. This approach made it easier for newcomers to understand ML models, showcasing how IA can make complex knowledge more accessible to general audiences. Beyond AI education, IA is also applied to real-world scenarios requiring dynamic visualizations. Focusing on real-time simulation scenarios, Savenije et al. [58] demonstrated an interactive visualization of real-time crowd movement in a museum context, illustrating applications in crowd simulation and management for educational purposes. Padwal et al. [49] further expanded the visualization scope by showcasing scenarios such as map-based learning, mathematical visualizations, and ML model interpretation in a mobile AR framework. These solutions underline the potential of immersive visualization tools as powerful aids for education.

5.1.2 IA platforms for collaborative learning

AI-supported IA can be integrated into XR platforms or tools for collaborative learning, in which communication and collaboration between multiple learners and educators may enhance the accessibility and effectiveness of education. For instance, Masneri et al. [32] proposed an interactive AR architecture that enables learners and educators to collaborate effectively. The platform integrates real-time data from learners, which is automatically visualized and analyzed, offering a dynamic and adaptive learning experience.

5.2 Manufacturing (A2)

Driven by modern industrial guidelines such as Industry 4.0/5.0 [69] and the Industrial Internet of Things (IIoT) [70], manufacturing is rapidly evolving toward intelligent and digitalized ecosystems that allow interconnected, autonomous operations and real-time data analytics. While AI has become a key component in IIoT, combining AI and IA has further enhanced manufacturing scenarios with remote inspection for process data, spatial structural data, and assistive maintenance for machines.

5.2.1 Process inspection

Inspecting manufacturing processes remotely is a critical phase of intelligent manufacturing. Deshpande et al. [33] presented an IIoT-based framework in AR for data communication from physical manufacturing processes to operators. The framework integrates technical advances such as AI, cloud computing, and smart sensors to digitize

manufacturing processes. Operators can monitor machine parameters and real-time performance by using IA in AR interfaces. Specifically, this framework supports predictive analysis of manufacturing data and provides corrective recommendations using Bayesian networks (BN). As analog gauges are widely used in traditional manufacturing scenarios, manually checking and recording data from gauges in manufacturing fields may be less effective. To address this problem, Althobaiti et al. [50] proposed a mobile AR application that automatically records and visualizes factory data. The application provides broad functions, from digitizing analog gauges to automating historical data storage and visualizing manufacturing trends. Focusing on the VA of abstract manufacturing data, Hoppenstedt et al. [61] demonstrated effective dimensionality reduction techniques to analyze scatters of high-dimensional production data.

5.2.2 Manufacturing environment inspection

While machine parameters and performance are important when inspecting manufacturing processes, physical environments may also complete the whole picture of manufacturing conditions and provide valuable insights for operators. Moreover, remote inspection may be necessary to avoid manufacturing risks for predictive maintenance of manufacturing environments. Iglesias et al. [51] proposed a photorealistic immersive system that allows users to analyze 3D environmental data remotely, demonstrated with a use case of finding crack patterns in a tunnel in a VR environment. For indoor environmental data inspection, Stedman et al. [44] proposed an immersive teleoperation system for monitoring the physical environment in real time. Robots with multiple sensors are used to collect data for immersive visualization, and 3D reconstruction of physical environments based on a point cloud of the environment is implemented to enhance immersion. Operators can affect the remote manufacturing environment via a teleoperation system.

5.2.3 Machine maintenance

Manufacturing processes often involve failure analysis and maintenance of machinery. Most IIoT-based intelligent manufacturing systems can troubleshoot and report errors (e.g., Ref. [33]), but machine maintenance is still labor-intensive and time-consuming. Researchers have explored providing

assistive systems based on AI and IA to address this problem. For example, Patibandl et al. [55] proposed a method for real-time tracking of machinery status using AR HMDs. AI techniques such as spatial mapping and localization are employed to detect machine artifacts, and assistive information is visualized in AR for real-time guidance.

Overall, six papers from the corpus demonstrate combining AI and IA to enhance intelligent manufacturing in terms of promoting efficiency and transparency. With the aim of providing digital systems referenced to the physical manufacturing processes, AR is often adopted for data visualization.

5.3 Smart healthcare (A3)

In the healthcare domain, analyzing medical data, including high-dimensional abstract data, imaging data, and medical instructions, is a critical step for clinicians to diagnose illnesses and provide treatments. IA with XR interfaces has provided new methods to manage, visualize, and interpret complex medical data for clinic decision-making. The integration of AI techniques and IA may provide more potential for smart healthcare applications.

5.3.1 Frameworks and techniques for IA of patient data

Our corpus includes a group of research efforts that implement immersive visualizations of patient data to support clinical decision-making. For instance, Lau et al. [39] proposed *VROOM*, an IA tool for assisting clinicians in analyzing cohort features of oncology patients. Further, they introduced game theory [30] into this analytical process and evaluated usability with a cancer dataset. Additionally, Velazco-Garcia et al. [48] presented an IA framework for medical imaging data with a holographic augmented reality interface. As medical data usually feature high dimensions, dimensionality reduction has been discussed frequently for immersive visualization. Hoppensted et al. [65] presented an interactive XR-based visualization prototype for high-dimensional patient data, in which AI-based voice recognition enables the natural interaction of analysts for visualization.

5.3.2 Data collection from multiple sources for city-scale healthcare networks

More recently, research has focused on developing city-scale intelligent healthcare systems that

connect patients, healthcare providers, and medical researchers. For example, Sornlertlamvanich et al. [29] outlined a multi-source data collection platform for city-scale healthcare systems. The platform involves data from various roles, including elderly individuals, healthcare providers, and other stakeholders such as insurance companies and restaurants. Such healthcare information systems include electronic sensors and AI detection, enabling data transfer between various analytical units to support intelligent decision-making. For example, personal health measurements of elderly individuals can be recorded to create health risk alerts for individuals and healthcare providers.

5.4 Urban planning (A4)

Urban design and planning focus on placemaking and shaping urban environments associated with geographical patterns and civic experiences. Therefore, a broad group of data types is involved in urban planning, such as meteorological data, civic data collected from personal mobile devices, and urban data such as building information, traffic data, and emission data [71]. Recent research has demonstrated the potential of XR and AI technologies to enhance data understanding and support design and planning through immersive experiences.

Our corpus identifies two studies using AI and IA for urban planning. One focuses on analyzing meteorological information using AR [41], while the other employs a VR-based analytical model for spatial information [56]. For the IA system for meteorological information [41], researchers presented a mobile AR application to visualize, analyze, and predict real-time wind speed and direction. Kampani et al. [56] proposed an analytical model *Perceptive Machine* to assist urban planning processes by mining, analyzing, and visualizing geospatial data in a virtual 3D space. However, evidence of using IA and AI for comprehensive urban management platforms integrating city-scale data across all subdomains remains limited. For example, Sornlertlamvanich et al. [29] proposed a city-scale data collection platform, but its primary focus is on enhancing smart healthcare applications rather than urban design and planning.

5.5 Assistive systems (A5)

Assistive systems cover a broad paradigm of leve-



raging influential technologies such as AI, XR, and smart devices to provide real-time guidance to humans for specific tasks. AI-integrated IA systems enable the natural exploration of complex tasks and provide multisensory experiences in assistive systems. For example, conversational AI agents can be integrated into XR to help humans analyze complex tasks and gain quick insights for further actions.

Research on assistive systems in our corpus focuses mainly on AR platforms and taking visual information as system input. Camera-based AI techniques solving computer vision (CV) problems, such as object detection, have shown the capability to capture real-world data and support analysis in virtual spaces. By incorporating these AI techniques, IA systems can analyze visual information from the real world via visual senses. Physical objects and user behaviors have been the data types explored for such applications. For instance, Büschel et al. [66] presented two AR-based information retrieval system prototypes with natural interaction techniques, including audio and gestures. Although the prototypes demonstrate the conceptual design of the information retrieval system to support the understanding of situated objects, the retrieved information contains only classification tags of objects lacking details. AI techniques also facilitate generating visual guidance in AR-based assistive systems. Castelo et al. [34] presented an AR-based assistive system that provided real-time task guidance and retrospective analysis. Multi-modal data, including audio, video, speech, and depth, are used as input for understanding the 3D environment and user behaviors in the assistive system. AI techniques are utilized to support environmental perception, analyze user behavior, and provide visual guidance. Task guidance is then represented via visual objects augmented into the camera-captured physical environment.

5.6 Disaster management (A6)

The field of disaster management often involves addressing societal emergencies and natural disasters, requiring analyzing and visualizing data from both public and natural environments. Two studies in the corpus include disaster management applications focusing on natural disaster management and mitigation. For natural disaster mitigation, Alarcão and Pestana [46] presented an architectural design of a

mobile AR-based platform for beach safety, where AR technology is used to visualize rip currents on mobile devices, and AI is used for hazard detection. Another study introduces an application that integrates XR and ML for visualizing seismic data and interacting with analytical results from ML algorithms [57]. This technology has the potential to be extended to visualize and analyze other forms of high-volumetric 3D data.

5.7 Sports events (A7)

XR has been widely applied in various live events, such as music festivals [72, 73], sports [74], and immersive tourism [75], primarily to enhance audience engagement or facilitate a wider audience reach unconstrained by a physical location. Because of the commercial implications and competitive dynamics of sports events, real-time data visualizations and visual analytics are typically used to augment audience engagement and deliver insights on player performance and match forecasts [76]. Additionally, pre-recorded sports events can provide historical data for formulating live strategies and training methods. Therefore, IA for sports analysis is an area that presents immersive visualizations of real-time or pre-recorded sports data in IEs, coming up with the integration of XR in sports events.

Our corpus identifies a research group focusing on using AI and IA for sports analysis. Wu et al. [40] explored using object detection techniques and AR to enhance user engagement in a hybrid sports event. Specifically, augmented information such as national flags and dynamic speed visualizations are presented on large displays or mobile devices with situatedness to the physical swimming tracks in a swimming competition, which is detected by CV techniques. Additionally, Lin et al. [26] proposed *VIRD*, a VR video analysis tool for providing insights for badminton training. Based on a badminton match video, users can analyze the 3D dynamic poses of players, ball trajectories, and game data in VR. CV techniques are applied to reconstruct the 3D dynamic scene. Other researchers have also proposed real-time IA solutions for onsite sports analysis. For instance, Iannucci et al. [37] proposed an AR application that tracks rowers' positions and stroke sequences in rowing. Visual feedback, including performance metrics and visual guidance for rowers, is presented to coaches and rowers for real-time analysis. Similarly,

CV techniques are used to extract motion data for further visualization and analysis.

5.8 Military communication (A8)

Timely and accurate decision-making is critical for military operations. Modern battlefields often involve large amounts of heterogeneous data, including geospatial information, civic data, and dynamic threat estimation. AI-supported IA has emerged as a powerful approach to enhance situational awareness, enable real-time decision-making, and support collaborative planning in military contexts.

Our corpus includes a military application using a multimodal XR framework integrating AI technologies [53]. This system leverages AI and immersive technologies to process multi-source datasets and present actionable insights in VR and AR environments. Additionally, multimodal interfaces are enabled to support natural interaction, such as voice commands, gaze tracking, and gesture controls. Despite the military context, this framework inspires future directions by highlighting IA systems' scalability and collaborative features for predictive analytics and cross-domain applications.

5.9 IA domain (R1)

Apart from application domains, a notable number of research efforts on AI and IA combination focus more on technical aspects of IA. The mainstream of IA technical topics has clustered around four issues: (i) design perspectives of IA systems, (ii) collaborative IA, (iii) situated analytics in IA, and (iv) user behavior analysis for IA.

5.9.1 Design perspectives of IA systems

IA design spaces involve critical issues, including specifications of display devices, immersive environments, interaction methods, visual representations, and spatial layouts. Our corpus includes a notable number of studies focusing on visualization techniques and interaction methods in AI-integrated IA systems. Visualization techniques such as parallel coordinate plots [38] and visual cues [43] have been explored as effective methods to support clustering and classification tasks. Besides, Wagner Filho et al. [67] evaluated the effectiveness of different dimensionality reduction methods for clustering tasks with immersive scatterplots. For interaction methods, prior research has investigated the potential of AI-supported interaction methods in IA tasks. For example, Hong

et al. [47] proposed a prototype of knowledge board interaction with ML assistants for complex analytical tasks. Additionally, Tahmid et al. [42] compared explicit and semi-automated clustering techniques for 3D spatial data clustering tasks, in which the results indicated that AI-assisted interaction exploration is preferred. There are also studies investigating design issues for specific IA tasks, such as spectral data analysis [28] and cluster-based flow pattern analysis [68]. These studies also provide valuable insights for general IA system design.

5.9.2 Collaborative IA

Collaborative IA systems enable multiple users to work jointly on analytical tasks in XR environments. Users can collaborate remotely or from co-locations. Two studies out of the corpus have addressed the research focus of the collaborative IA system. Benk et al. [45] assessed user performance with an IA system regarding task work and teamwork in co-location scenarios. The results show the benefits of collaborative efforts on VA tasks, especially for complex tasks that require collaboration among users with different backgrounds. Different from this study on co-location collaboration, Fanini and Gosti [27] introduced a new generation of remote collaborative IA through a webXR that integrates AI for immersive and synchronous data analysis in 3D environments. WebXR has been examined as an advantageous platform for remote collaboration, demonstrated by volumetric data analysis in VR. These developments could foster deeper interaction and understanding in collaborative analytics workflows.

5.9.3 Situated analytics in IA

Situated analytics augment visualization and data insights into physical scenes or objects, enabling intuitive and context-aware decision-making. The IA research community has explored situated analytics a lot, while in our corpus, two papers integrate AI techniques with situated analytics. Focusing on tabular data, Burley and Nandi [64] introduced an AR framework *ARQuery* for data querying and interactive analysis. It allows users to interact with both physical and digital tabular data through haptics like tapping and swiping. CV techniques are used to capture physical tabular data as the input to the situated analytics system. Besides, using AI techniques can also enhance multisensory experiences in situated analytics. For instance,

Naik and Johnson [36] provided *PSA*, an MR platform for exploring recorded events, such as conversations. It immerses users into reconstructed spatial and temporal contexts using 3D models and overlaid transcribed speech. Through multimodal interaction methods, such as time sliders and gesture-based navigation, users can interactively analyze interpersonal dynamics and event sequences. In some dynamic scenarios of situated analytics (e.g., sports analysis in AR), automatic digital label placement in AR with references to physical objects has been an emerging research field supported by AI techniques such as deep reinforcement learning [77]. However, our corpus identifies little evidence of such applications for analytical tasks.

5.9.4 User behavior analysis for IA

The included studies have demonstrated the evaluation of the usability and user experience of IA systems by user behavior analysis. Specifically, interactive exploration of immersive environments and cognitive activities were recorded to support direct assessment of the usability and level of immersion of IA systems. Existing research has provided insights into this area. For example, Duvivier et al. [31] proposed a framework for analyzing trajectories and events of user behaviors in an IA system. Batch and Elmqvist [62] presented a pipeline for analyzing user actions in videos in VR systems based on ImAxes [78]. Camera-based object tracking is used to extract behavioral patterns from videos. By implementing user behavior analysis in an IA system with two groups of participants with different levels of expertise, they demonstrated a way to evaluate the usability of the IA system for different user groups.

5.10 AI domain (R2)

The included studies have demonstrated a popular research direction where IA can be used to visualize AI models and support interactive execution for the AI domain. Enhancing explainable artificial intelligence (XAI) is the primary purpose of visualizing AI models in immersive environments. Research efforts have shown various AI models and visualization techniques in practice. Douglas et al. [60] introduced an immersive visualization of the saliency data generated from a deep reinforcement learning (DRL) agent. Similarly, Meissler et al. [63], Bellgardt et al. [54], and Nagasaka and Izuhara [52] have presented different visualization solutions, such as

node-link diagrams for deep neural networks despite differences in target user groups. However, since Meissler et al. [63] introduced their visualizations to enhance knowledge learning in the context of AI, this study has been classified in the *Education/Training (A1)* category.

On the other hand, immersive visualization has also been used to enhance interactive ML (IML), which aims to incorporate human intelligence into ML training processes. Users can compare the outcomes of ML models against the desired outcomes and provide feedback to improve the ML models, thus forming a human-in-the-loop process. Ferrario et al. [59] first presented an AR-based system allowing collaborative analysis of training ML processes by ML engineers and domain experts. The shared workspace of the system enables users with different levels of expertise to interact with the same ML model and communicate with each other, which can enhance effective model building. More specifically, Cordeil et al. [35] proposed an immersive IML dialogue in VR for 3D point cloud classification, which has presented a novel interaction method using VR controllers. In this work, 3D point clouds are visualized in a VR environment, and users can select point clouds in a VR environment as minimal input for ML models. The model outcomes are also visualized so that users can compare them to classification ground truth, thus refining the ML models. The rich graphical representations of immersive visualizations also enhance engagement, thereby improving the explainability of ML models.

5.11 Summary

As we have shown in Section 5, although not all included studies are featured as application studies, the research focus of combining AI and IA has gravitated towards several application areas, such as *Manufacturing (A2)*, *Smart Healthcare (A3)*, *Education/Training (A1)*, and *Sports Events (A7)*. There are also a notable number of included studies (18/43) having primarily theoretical or methodological focuses, categorized into *IA Domain (R1)* and *AI Domain (R2)*. For *IA Domain (R1)*, design perspectives of IA systems, such as interaction methods and visualization techniques, are the primary research focus, while interactive visualization of AI models is a primary focus of *AI Domain (R2)*.

While several studies in our corpus focus on

collaborative IA applications that target multiple user scenarios, most of these applications are associated with situated analytics based on AR technology. In these applications, AR is used to visualize data with spatial references linking virtual visualization spaces and real-world objects or environments. For instance, application directions such as *Manufacturing* (A2), *Assistive Systems* (A5), and *Sports Events* (A7) mainly involve IA solutions using AR technology to incorporate visual references. From a data type perspective, despite the high-dimensional data involved in application categories such as *Education/Training* (A1) and *Smart Healthcare* (A3), the identified application directions involve a majority of IA solutions for geospatial data [34, 40, 41, 50, 51, 55, 56, 61, 66]. Also, collecting and storing heterogeneous data from multiple sources is also a preliminary task for IA systems applications involving city-scale data analysis, such as applications in *Smart Healthcare* (A3) [29], *Urban Planning* (A4) [56], *Disaster Management* (A6) [46], and *Military Communication* (A8) [53].

6 AI in IA

6.1 Pipeline

This section summarizes the research efforts that utilize AI in IA. As existing research shows limited exploration of a comprehensive presentation of the AI techniques integrated into IA systems, we propose an IA pipeline with potentially integrated AI techniques

(shown in Fig. 4) based on transformed knowledge from traditional VA models [19, 79, 81, 82] and their evolutions with AI [20, 21, 23], as well as relevant IA models [3, 80] to map research efforts in this field, as shown in Table 5.

Visualization and VA pipelines provide a strong foundation for developing IA pipelines. Ltifi et al. [82] conducted a comprehensive survey of VA models, offering a comparative framework for selecting models relevant to our IA pipeline. Among these, Van Wijk et al. [81] introduced a basic VA pipeline that emphasizes iterative user analysis and knowledge generation, establishing a core structure for knowledge workflows. Building on this, Keim et al. [79] detailed transitions between data, visual representations, patterns, and knowledge. Notably, their pipeline separates an automatic data analysis loop from visual data exploration, inspiring the potential integration of AI within the automatic data analysis loop. Sacha et al. [19] further extended the VA model by incorporating a human action loop, enabling knowledge generation through interaction with visualizations and data patterns.

Recent research on integrating AI and visualization has also revisited these models and extended some for better integration. Wang et al. [20] extended the VA knowledge generation model by Sacha et al. [19] by adding interaction, execution, and intelligence optimization loops to support human-AI collaboration. Similarly, Nazemi [21] proposed a task model for AI-driven knowledge extraction

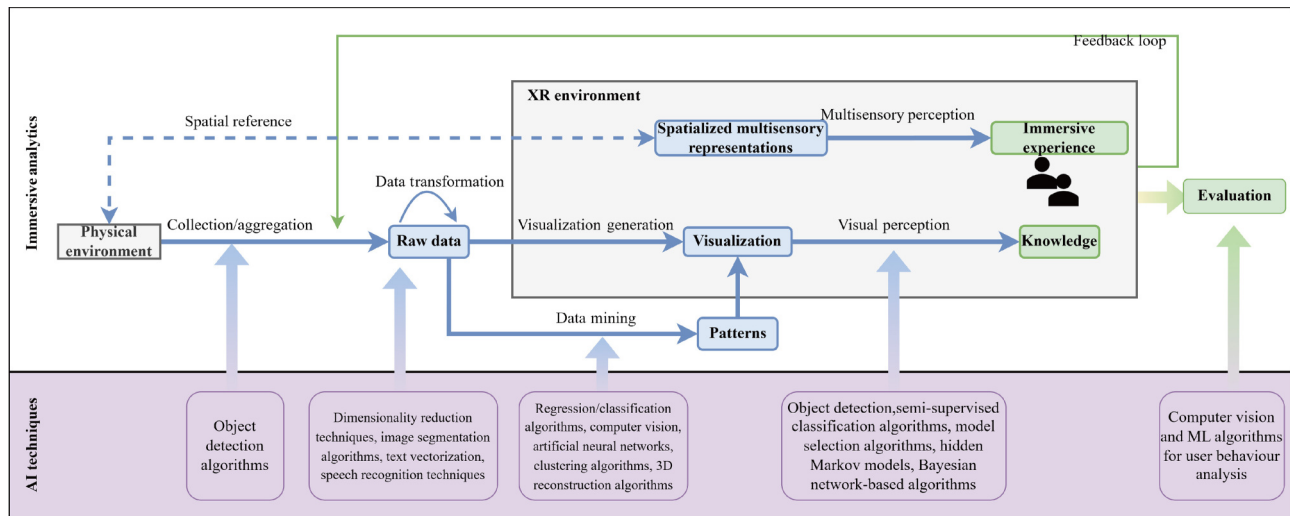


Fig. 4 AI techniques integrated into key stages of the IA pipeline. The IA pipeline is based on the conventional VA model proposed by Keim et al. [79] and IA architecture proposed by Marriott et al. [80].

Table 5 Comparison of VA models, VA models with AI, and IA models by model types and key features

Group	Reference	Model type	Key features
VA models	Van Wijk et al. [81]	VA pipeline	- Foundational VA pipeline - Highlights iterative user interaction with data and visualization
	Keim et al. [79]	VA pipeline	- Adds automated data analysis loop - Separates data mining from visual exploration
	Sacha et al. [19]	Knowledge generation loop	- Specifies human actions in knowledge generation
VA models with AI	Wang et al. [20]	Knowledge generation loop	- Integrates AI into knowledge generation loop for human-AI collaboration - Adds interaction, execution, optimization loops for AI
	Nazemi [21]	Task model	- Identifies actions and targets for VA tasks - Includes explainable AI and knowledge generation tasks
	Yang et al. [23]	Visualization pipeline	- Maps AI models to visualization pipeline
IA models	Marriott et al. [80]	Abstract IA architecture	- Introduces XR-specific collaboration architecture
	Kraus et al. [3]	Task model	- Defines guiding scenarios of IA applications
	Ours (Fig. 4)	IA pipeline	- Defines IA pipeline with multisensory representations - Maps AI techniques in the pipeline

in VA, specifying user actions and analytical tasks. Yang et al. [23] mapped AI foundation models into a generic visualization pipeline based on the information visualization model introduced by Card et al. [83], demonstrating how foundation models can be key to stages in visualization processes. However, IA models are relatively rare; thus, the AI integration model in IA has also yet to be explored. Marriott et al. [80] proposed an abstract architecture of collaborative IA applications in the XR environment, in which the physical environment and multisensory data presentations were involved for immersive experiences. In identifying the unique value of IA compared with conventional VA, Kraus et al. [3] presented four guiding scenarios, including situate analysis, spatial data and spatial tasks, collaborative tasks, and immersive presentation. These guiding scenarios can provide insights for defining IA tasks that AI can support.

Our IA pipeline builds on key steps from conventional VA pipelines, incorporating features specific to XR environments and IA design frameworks. Inspired by Marriott et al. [80], it integrates references from physical environments into XR contexts to highlight spatial information mapping in specific IA applications. The core knowledge generation steps are drawn from the VA pipeline by Keim et al. [79], with feedback loops expanded to include immersive experiences enabled by multisensory data representations. Based on IA design principles, the pipeline integrates an evaluation phase that provides critical design feedback. Building on this foundation,

we explore how AI techniques can be applied in IA systems. Table 6 summarizes these findings across five key phases.

6.2 Data collection (P1)

Data collection is generally recognized as the first phase of AI pipelines. This differs from most conventional VA pipelines in which data transformation is the initial phase [82]. For non-real-time data analytical tasks, data is collected beforehand and readily available. However, incorporating dynamic data feeds and real-time visualizations is critical for IA systems. Therefore, data collection is included as an initial phase of IA pipelines.

AI, with capabilities such as object detection, tracking, and synthesizing information from sub-domain data, often supports the data collection phase, especially for collecting visual, auditory, or multimodal information from the physical environment. AI-based object detection algorithms are the most typical AI methods for collecting visual objects or environmental information from the physical world. Such AI-based data collection is significantly applied in AR-based situated analytical applications to detect the referenced physical objects or scenes for situated visual effects [64]. For example, IA applications in manufacturing [33, 50], sports analysis [26, 37, 40], and AR assistive systems [34] are often based on AR interfaces to present visualizations situated on detected physical objects, motions, and environmental features. In IA applications for sports analysis, athletes' motions and gestures are usually

Table 6 AI techniques identified from our corpus support IA in five phases of the IA pipeline

Phase	Perspective	AI techniques involved	Description	Count	Reference
Data collection	Capture physical information	Object detection algorithms	Visual or multimodal information is automatically collected by AI techniques from one or multiple sources in the physical environment or objects.	9	[26, 29, 33, 34, 36, 37, 40, 50, 64]
	Filter/downsample the collected data	Dimensionality reduction techniques: PCA, t-SNE, UMAP, Autoencoder, etc.	Dimensionality reduction techniques are used to filter high-dimensional data.	6	[30, 39, 56, 61, 65, 67]
Data transformation	Normalization	Image segmentation algorithms/text vectorization algorithms	Image segmentation algorithms and text vectorization techniques are used to normalize the original data.	2	[47, 48]
	Modality transformation	Speech recognition	Speech recognition toolkits such as <i>Google Speech Recognition API</i> are used to convert audio data into text format.	1	[36]
	Enrich visual mapping	Regression models, deep learning algorithms for predictive analysis, CV toolkits, classification algorithms such as logistic regression and random forests, etc.	Typical classification models or clustering algorithms extract patterns and add additional visual effects to the original visual mapping.	11	[34, 35, 38, 41, 43, 45, 46, 49, 51, 55, 57]
Knowledge generation	Extract patterns for visualization	Decision trees, linear regression models, support vector machines for classification tasks, clustering algorithms, 3D reconstruction algorithms	Patterns extracted by AI models from the data mining process are components mapped to visualizations.	4	[32, 44, 68, 84]
	Add automation to interactive exploration	Semi-supervised classification algorithms, model selection algorithms	Enhancing interactive exploration	4	[28, 33, 34, 53]
IA evaluation	Generate guidance for visualization understanding	Object detection, hidden Markov models, Bayesian network-based algorithms	AI generates information guidance for decision-making based on visual objects and status in AR systems.	2	[42, 47]
	User behavior analysis	CV and ML algorithms	AI support user behavior analysis to evaluate IA systems.	3	[27, 31, 62]

the objects to detect and track. For instance, Wu et al. [40] presented an AI application for live sports events which tracked swimmers' positions in a swimming pool for further situated visualization steps. Tracking is based on in-site cameras and CV techniques. After analysis, national flags are situated on the swimming pool to enhance audience engagement. Similarly, Althobaiti et al. [50] presented a mobile AR application that uses CV algorithms to detect and transfer analog gauges into digitalized measurements.

AI-based data collection can also facilitate IA by constructing platforms or systems for multimodal and multi-source data collection. For example, Naik and Johnson [36] implemented an always-listening AI agent to capture human conversations in a collaborative situated analytics scenario in VR and MR environments. The AI agent functions together with motion capture by object detection, monitor screenshots, and onsite video. The AI-aided multimodal data are analyzed to identify patterns of user behavior in collaborative IA. Instead of directly utilizing AI techniques in data collection, Sornlertlamvanich et al. [29] proposed a novel AI platform for collecting and sharing city-scale multimodal data, which provisions a combination of IA systems at different data scales.

6.3 Data transformation (P2)

Although immersive technologies such as VR and AR have improved the capability to display large amounts of data compared to traditional 2D displays, they still have limitations in visualizing high-dimensional data directly. Thus, dimensionality reduction has been a crucial step for immersive visualization. Additionally, the data collected from the physical world are often descriptive of physical objects or events. Data pre-processing methods such as filtering, normalization, and transformation may provide structured data for later procedures. With advanced computational capabilities, various AI techniques have enhanced data transformation in this phase. Specifically, AI-based dimensionality reduction methods [30, 36, 39, 61, 65, 67], data normalization [47, 48], and data modality transformation [36] are key examples.

For data transformation, most analyzed studies include dimensionality reduction steps. For example, Lau et al. [30, 39] implemented various dimensionality reduction techniques such as principle component analysis (PCA), t-distributed stochastic

neighborhood emulation (t-SNE), uniform manifold approximation and projection (UMAP), non-negative matrix factorization (NMF), and autoencoders, to transfer complex genomics data to a VR space. Similarly, Hoppenstedt et al. [61, 65] utilized PCA for simplifying high-dimensional data and exploring data correlations in an immersive 3D space. Despite the application focus, the proposed prototype of IA with dimensionality reduction is generalizable to gain understanding in any high-dimensional data exploration. Specifically, the information loss during dimensionality reduction is computed as the remaining covered variance to compare the effects of different dimensionality reduction techniques. Wagner Filho et al. [67] focused on evaluating dimensionality reduction effects by comparing systematic errors of transforming high-dimensional data into 2D or 3D formats and the perceptual errors by humans using desktop displays and HMD. The results of their user study show that perceptual errors due to dimensionality reduction can be generally ignored, but transforming high-dimensional data into 3D space can result in a lower information loss. Therefore, the knowledge generated from IA with dimensionality reduction can outperform traditional VA with 2D display spaces.

Data normalization is a critical data pre-processing step that unifies data formats regarding numerical ranges and image segments for better visual mapping in IA. In our corpus, AI techniques such as image segmentation algorithms and text vectorization algorithms are applied in data normalization phases. Typical examples have appeared in IA-based healthcare systems [47] and collaborative IA scenarios [48]. For example, Hong et al. [47] used an NLP toolkit to preprocess textual data and vectorize them using Doc2vec algorithms in an ML-assisted knowledge board system [47].

Modality transformation transforms information between different modalities, such as text, video, and auditory. AI-based techniques for data transformation have been well-explored and have shifted into the IA domain. For example, Naik and Johnson [36] used the Google Speech-to-Text API to transform collected audio data into text formats for further visualization steps in a collaborative IA scenario. In this case, the transformation between audio and visual modalities enables the IA system to reduce effort in recording

user conversations and visualizing key information from the text.

6.4 Visual presentation generation (P3)

6.4.1 Methods

The visualization phase of the IA pipeline maps structured data into visual structures such as scatterplots, curves, and node-linked diagrams, and it includes presenting visual structures in comprehensive views in immersive environments. AI, with its capability to analyze complex data, can be used to enhance visualization generation. According to different analytical tasks, the integration of AI into the IA pipeline can be performed by two types of methods: (M1) AI generates additional visual content or effects, and (M2) AI replaces direct visual mapping by extracting patterns from structured data: see Fig. 5. On the other hand, understanding AI as a complex cognitive process often benefits from IA. Our corpus also identifies such research examples (shown in Table 4: R2). AI models and architectures are the primary visual content in IA. Users can interact with AI architectures and model training procedures by interactive exploration in IA to understand the AI context. As this section highlights research examples using AI in IA, IA for AI research examples are omitted for clarity.

6.4.2 AI generates additional visual effects

To provide additional visual structures, AI models and algorithms extract patterns from the pre-processed data and then map them with visual effects, including visual content and style. Together with the

visualization of original data structures, the enriched visual effects present important information to users for understanding. Situated VA with references to geospatial information can benefit from AI by adding augmented summarization to physical objects or scenes [41, 46, 51, 55]. For example, with a geospatial analysis focus, Harbola et al. [41] proposed mobile AR applications for predictive analysis of wind. A pre-trained regression model predicts the wind direction and speed, and direction labels are superimposed onto the physical scene so that users can conveniently perceive the wind situation on site. Similarly, Alarcão and Pestana [46] detected the presence of rip currents using DL algorithms to foresee the potential danger posed by such currents. Visual representations of the hazard plume are generated accordingly. Moreover, typical examples of enhancing situated VA with AI have clustered in failure analysis of manufacturing devices and tools in industrial applications [51, 55]. CV algorithms are often integrated into display devices to detect the spatial referents from the physical world. Specifically, Patibandla et al. [55] proposed a VR solution for remote failure analysis of a tunnel. 3D reconstruction of the tunnel in a VR environment bridges the gap between the augmented 3D spatial failure structures and the physical tunnel referents.

Other analytical tasks using AI techniques or toolkits have also helped generate extra visual structures in IA. Exploring data [38, 49] and better-presenting data representatives [57] are two main focuses. Bobek et al. [38] presented parallel coordinate plots in VR for multidimensional abstract data, in which data and feature importance are visualized based on a set of explainable AI methods, such as logistic regression classification and random forest classification. The parallel visualizations of the original dataset and feature importance can be integrated into any data analytical process to enhance understanding. Instead of focusing on visual context, Lawton et al. [57] overlaid color coding and transparency onto 3D spatial volumetric data in VR. While 3D seismic data are visualized using volumetric rendering techniques in VR, visual effects are generated from ML certainty results. Therefore, the visualization addresses the higher importance of data with higher ML certainty values, thus improving the understanding of 3D spatial data [38].

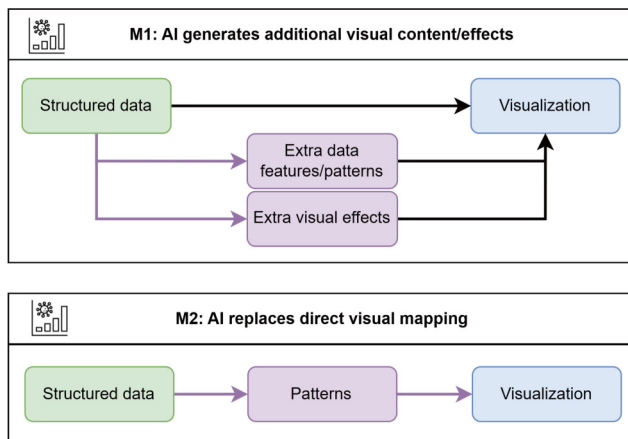


Fig. 5 AI in immersive visualizations in two ways: (M1) AI generates additional visual content or visual effects from structured data; (M2) AI replaces direct visual mapping and extracts patterns from structured data. Purple highlights the AI contribution in each method.

6.4.3 AI replaces direct visual mapping

In the IA pipeline, visual mapping transfers structured data into various visual structures using visualization techniques such as scatterplots and node-linked diagrams. In this phase, structured data can be utilized for advanced analytical tasks supported by AI techniques, and the results can be visualized to enhance analysis. Therefore, there is no traditional visual mapping from the processed data inputs; instead, a higher-level set of data features extracted by AI is mapped to visual structures. For example, Masneri et al. [32] proposed cleAR, an IA system for educational analytics and collaborative learning, in which a wide range of ML toolkits and algorithms are integrated to analyze learning performance. The analytical results are visual content for students and teachers in AR environments. Specifically, teachers without an AI background can customize the AI framework in cleAR to achieve visual analytical goals, so emphasizing more explainable AI models, such as decision trees or linear regression models, despite the capability and accuracy of data analysis. Toujani et al. [84] applied a support vector machine (SVM) to classify people in natural disasters using social data, including text, images, video, and location. The visual content combines the location and risk measurements generated from classification results. In this IA system, only people identified as at-risk are highlighted in map-based visualizations. Similarly, Roy et al. [68] extracted spatiotemporal 4D flow data patterns using a cluster-based method. The visualization content consists of velocity vectors at each 2D/3D grid point based on the clustering results of the k -means++ algorithm [85], and users can interact with the clustering results with haptic feedback. Focusing on transferring physical spatial information into a VR environment, Stedman et al. [44] presented *VRTAB_MAP*, an immersive teleoperation framework built upon a graph-based simultaneous localization and mapping (SLAM) toolkit for large-scale 3D reconstruction. The framework takes camera-captured images of the physical scene as input and computes a point cloud 3D reconstruction and mapping of the scene based on SLAM algorithms, together with sensor synchronization and graph optimization. AI techniques, including the SLAM algorithms, are critical components in spatial data mapping from the physical world to VR environments.

6.5 Knowledge generation (P4)

Knowledge generation in IA is a human cognitive process involving the interactive exploration of visual content. AI can support knowledge generation from immersive visualization by adding automation to the interactive exploration processes and generating guidance for visualization understanding processes.

6.5.1 AI automation for interactive exploration

In the interactive exploration phase, AI techniques minimize the need for user input to IA systems without affecting the performance of complex analytical tasks. For example, annotating large amounts of data with human intelligence in the physical world can be time-consuming and error-prone, especially for large amounts of spatial data, which makes it hard to perceive the features without visualization. One possible solution is to combine immersive visualization with data annotation facilitated by AI techniques. For example, Hong et al. [47] presented *Talk2Hand*, an interactive IA framework with an ML assistant, in which a textual data classification task was deployed with a semi-supervised learning strategy. Users are first required to interact with a visualization of the textual data by labeling the group of a small part of the data content, then an SGD classifier [86] is applied to classify the remaining data. Moreover, Tahmid et al. [42] presented the same idea of combining human intelligence with a Dirichlet process mixture model (DPMM) for semi-automatic clustering. From the user study, the researchers found that implementing AI techniques in the interactive exploration phase may reduce human intervention and allow humans to gain insights from spatial data structures efficiently. Although various AI techniques have been applied in IA systems to support understanding by adding autonomous prediction or interpolation capabilities, human expert judgment is critical to understanding not only data patterns and insights but also autonomous methods, especially when AI-based autonomous analytics produce undesired outcomes. Our corpus also identifies research examples that use immersive VR environments as interfaces to enable human-AI collaboration in complex analytical tasks such as spectral data in medical contexts while allowing real-time model selection to explore optimal ML algorithms [28]. Analysts can recognize patterns and visualize thresholds

crucial to reducing erroneous outcomes from ML algorithms. This study compares the human selection of ML models based on null augmented regression eigenvalue (NARE) in a VR environment with a real-time model selection algorithm, model diversity prediction similarity (MDPS). The results indicate the advantages of immersive environments in visualizing model selection processes and leveraging human intelligence. Moreover, adding automation to interactive exploration by AI enhances the natural interactions between users and IA systems. For instance, users can interact with visualizations in IA systems via natural language if NLP is integrated. Mittermeier et al. [53] have shown such integration in a multimodal IA system for military decision-making.

6.5.2 AI guidance for visualization understanding

In IA systems, some visualizations present computer-based analytical results while leaving the visual information synthesis and decision-making processes to humans. Thus, with its feature extraction and information generation capability, AI can synthesize visual content from IA systems and generate user recommendations. Existing efforts have shown this usage in online task guidance scenarios [34]. For example, Castelo et al. [34] in an AR-based task guidance framework proposed the use of object detection and a hidden Markov model (HMM) [87] based approach to predict subsequent user actions, which can be potentially used in medical training and user behavior analysis scenarios. Moreover, the AR-based visualization system with integrated AI can improve human performance by reducing cognitive load. Similarly, Deshpande et al. [33] deployed a Bayesian network to predict manufacturing parameters in an immersive data communication framework. In this study, users are able to customize the desired outputs of the manufacturing system after the AR application recognizes current manufacturing parameters using the CV toolkit. Based on user inputs, the BN is used to predict the required parameter values so that users can adjust the manufacturing conditions in the physical world or the desired outputs.

6.6 IA evaluation (P5)

IA evaluation can provide valuable design feedback to IA system developers, which covers a wide range of evaluation methods, including qualitative and quantitative analysis. AI architectures and model

training processes are often regarded as complex. Therefore, in some IA systems, AI content can be analyzed in IA system. There is some research that sets up AI content as the user tasks in IA evaluation [27]. Besides, AI has been used to understand user behavior in IA systems to uncover users' interaction patterns, for evaluating the usability of IA solutions. For example, Batch and Elmqvist [62] used CV and ML algorithms to analyze user actions in a VR-based IA system. Their methodology involves capturing video footage of user interactions, which is then processed to identify features such as movement patterns and biometric data like pulse and pupil dilation. The extracted data help to evaluate the IA environment's effectiveness by correlating user actions with their self-reported experiences. This allows for a deeper analysis of how design elements influence user satisfaction and performance. Alternatively, Duvivier et al. [31] explored the possibility of AI-facilitated in-situ analysis of user behavior. Based on an established VR platform, they proposed to train an encoder to analyze hybrid sequential data (trajectory and events) generated from interaction with a VR environment.

6.7 Summary

Following an updated IA pipeline based on the conventional VA model proposed by Keim et al. [79], the main methods of integrating AI techniques in IA are illustrated in Fig. 4. Given Table 6, the primary focus of integrating AI into IA is to leverage AI advances in immersive data visualization, including workflows from data collection and data transformation to visual presentation generation. The evidence from these phases indicates an AI4VIS research trend, which involves employing AI techniques to aid user tasks like data enrichment and analysis, with the results then used as content for visualization in IA. Besides, the corpus identifies a notable number of studies on using AI to support knowledge generation and IA evaluation processes. It demonstrates an emerging direction that combines human intelligence and AI in complex data analytical tasks and improves IA system designs.

7 Challenges and opportunities

This section highlights key findings and formulates future directions aligned with the current trends of IA with integrated AI. Our analysis, informed by a detailed examination of individual studies and a

comprehensive synthesis, highlights the state-of-the-art technological advances in the intersection of AI and IA. From a general perspective of IA research and its integration with AI techniques, this study identifies and categorizes four challenges and seven opportunities for future research.

7.1 Challenges

Four challenges and limitations are identified from the information synthesis based on the corpus and our knowledge. These include issues regarding types of applied AI techniques, degree of integration of AI and IA, task sharing in AI-IA integration, and user behavior in IA.

7.1.1 Lack of emerging AI techniques applied to IA

The results from our corpus indicate an absence of the application of emerging AI techniques, such as large language models (LLMs) and other generative AI models, within IA systems. Previous research on combining AI and IA has mainly concentrated on conventional ML techniques or DL models. Besides, the emphasis on using AI techniques in IA appears to support data collection, data transformation, and visual mapping phases, which stay in the same paradigm as VA and leave the immersive visualization spaces less explored. Therefore, this challenge lies in adopting advanced AI techniques and models in IA systems. For example, integrating LLMs into IA systems may enable multisensory experiences by supporting natural language interaction, automated insight generation, and personalized adaptive visualization in XR environments.

Based on our knowledge, one key reason for this challenge is the inherent difference between the paradigms of 2D and 3D visualization spaces. While AI technologies have addressed various VA tasks with large datasets in formats such as text, images, video, or relational databases, conventional visualizations are in 2D spaces. IA, however, leverages its strengths in processing and visualizing data in 3D spaces. Most AI models, including generative AI and DL architectures, are optimized for processing structured or unstructured data in 2D spaces and lack the adaptability to handle or generate insights in 3D environments seamlessly. For example, CNNs are inherently designed for 2D-pixel grids for image analysis. This disparity creates a significant barrier when integrating existing AI models into IA

systems. Thus, they require substantial modification or extension (e.g., 3D CNNs or volumetric approaches) to work in IA. Similarly, LLMs, while powerful for textual data processing, do not inherently support the spatial reasoning required for 3D data interpretation or interaction. Therefore, technical innovations by the AI research community specifically for 3D data visualization and redefining the design framework of AI-supported IA may address this challenge.

7.1.2 Limited integration level of AI and IA

Despite all the research into combining AI with IA identified in our corpus, this review finds that existing examples superficially focus on using AI to advance IA (AI4IA), using IA to enhance XAI (IA4AI), or using synergy to develop intelligent applications (AI-IA collaboration). However, deeper integration of AI and IA is limited, where AI and IA function in parallel workflows within the same visualization spaces. For instance, in our application analysis (RQ1), while the (R2) *AI domain* accounts for a number (6/43) of applications, where AI model parameters are visualized and analyzed in XR spaces with various visual representations, the AI architectures and model types are pre-selected and not configurable.

Current research attempts to address this challenge by introducing interactive environments for AI training processes (e.g., Refs. [35, 59]) or by visualizing model selection processes in immersive environments (e.g., Ref. [28]). By visualizing AI model selection processes in IA, analysts are provided with a number of AI models that can solve specific VA tasks and select optimal models. However, such provided models are still limited options. On the other hand, users can interact with model training processes with handheld controllers, gaze-based controllers, or haptics. However, these implementations still require significant prior knowledge of both AI techniques and IA systems to design and present AI models effectively in immersive environments. As a result, the integration remains constrained, particularly for non-expert users. Therefore, future research may provide explicit, dynamic representations of how data evolves through AI processes to bridge analysis and decision-making. Instead of having a standalone IA system for AI models, integrating interactive AI model visualization as a sublayer of IA systems may help analysts work with a wide range of AI models with little knowledge barrier.

7.1.3 Task sharing in AI-IA integration

User tasks in IA often involve initial data exploration, visualization, and analytical reasoning. Integrating AI techniques can significantly enhance these processes by automating repetitive and computationally intensive tasks, allowing users to focus on higher-level decision-making and interpretation. Specifically, our analysis of AI techniques in IA (RQ2) shows that AI techniques can streamline data preparation through automated data collecting, transformation, and feature extraction, allowing users to focus on data exploration and visualization phases. However, guidance and best practices for task sharing in human-AI collaboration in IA systems have yet to be explored in detail.

As knowledge generation in IA is a cognitive process, users gain insights from visualizations by interactive exploration. Prior research has shown examples of adding semi-automation or complete automation to specific tasks in IA processes, such as scatterplot analysis [42] and *Talk2Hand* [47]. Although AI techniques can replace human effort in specific steps to enhance efficiency, interactive exploration may not be skipped for the knowledge generation process but can be supported by AI techniques. Therefore, completely automated IA systems are merely optimal solutions.

From a broader field of human-AI collaboration, some research efforts may inspire its further exploration in IA systems. For example, Gupta et al. [88] proposed to construct an interdisciplinary research domain of collective human-machine intelligence and outlined the research agenda, including the creation of novel AI agents with collaborative features with humans. Besides, data storytelling also makes sense for knowledge generation; generative AI models such as LLMs make data storytelling more accessible. XR interfaces provide new possibilities for presenting multi-sensory storytelling to enhance visual understanding [89]. All these research efforts suggest new ways of exploring best practices of organizing human-AI tasks for better IA systems. Therefore, we see such problems in human-AI collaboration in IA as an open area for further exploration.

7.1.4 AI-supported user behavior tracking in IA

User behavior tracking may provide valuable information for presenting immersive, personalized

IA experiences and refining evaluation methods. Tracking user behavior in IA tasks, such as navigation paths, gaze movements, facial expressions, and physiological reactions, can provide user information to IA systems. Thus, IA systems can adapt visualizations and analytical workflows to individual user preferences. Besides, user behavior tracking provides valuable metrics for evaluating IA systems, thus identifying improvements for IA system designs.

Although AI has shown advances in collecting and analyzing user behavioral data in XR environments [90–92], integrating AI-supported behavior tracking into IA practices remains challenging. One primary concern is the ethical implications of tracking and sharing user behavior data. While AI can mitigate privacy concerns by automating data collection and reducing human involvement, it may introduce new challenges, such as algorithmic bias and transparency issues. Although AI may relieve privacy concerns by excluding human participation during data collecting, using AI to process such data may introduce new problems. Therefore, this problem may be addressed by proposing trustworthy AI solutions prioritizing ethical data handling, user consent, and accountability.

Currently, the IA community evaluates system performance primarily through use case demonstrations and user feedback, employing both qualitative and quantitative methods. Metrics such as task accuracy, completion time, comprehension, and understanding are commonly used [17]. However, these evaluation processes are often time-intensive and susceptible to research bias due to limited implementation conditions or participant numbers. Moreover, such evaluations generally collect data after participants have experienced the IA systems, which results in cognitive bias as participants may have little impression of specific measured dimensions. Despite the AI community's advances in analyzing user emotional behaviors—such as facial expressions [93–95] and psychological feedback on visual aesthetics [96, 97] in immersive and non-immersive environments, our corpus reveals a lack of studies incorporating such efforts into IA evaluation methods, which indicates a limited research focus on developing real-time IA applications with user satisfaction.

7.2 Opportunities in AI-IA integration

With respect to AI-IA integration, the following three opportunities are identified for future research,

targeting the development of more advanced AI-assisted IA applications with higher automation levels.

7.2.1 Generative AI models for IA

Deeper integration of AI and IA is necessary to enhance the efficiency and immersive nature of analytical experiences. Automated AI capabilities are able to simplify the design and implementation of IA systems and provide more intuitive visual elements for users. One promising approach is to utilize generative AI models to create visual content and styles in IA systems. Generative AI has the potential to streamline the entire workflow, from data processing to visualization generation, by infusing creativity, assistance, and automation into the visualization process [98]. While some applications are exploring the direct use of generative AI models for creating immersive visualizations, the AI community has proposed tools such as *Point-E* [99] and *NeRFs* [100] to assist in generating complex 3D shapes and structures from text prompts or 2D images. Prior research has also explored an AI-supported way to enhance efficient transformation from the physical world to VR/AR spaces, which contributes to presenting realistic environmental features to users with an immersive experience. For example, Bautista et al. [101] have proposed *GAUDI*, a generative AI tool for generating a 3D virtual environment with spatial reference to physical environmental data. Although these applications are not dedicated to immersive visualization processes, we envision that similar research efforts transiting to IA domains may unlock unprecedented possibilities.

7.2.2 AI-supported knowledge generation in IA

Existing studies have explored integrating AI techniques into the knowledge-generation process of IA workflows by providing task guidance [42, 47] or enhancing interactive exploration [33, 34]. However, this research direction has not been explored enough with recent AI advancements and novel interaction techniques. On the one hand, AI can support knowledge extraction from immersive visualization, thus accelerating human visual perception processes. For example, when users experience a large-scale node-link diagram visualization in VR spaces, advanced AI models such as CNNs, vision transformers (ViTs), and 3D convolutional neural networks (3D-CNNs), along with techniques like feature pyramid networks (FPNs) and region-based convolutional neural networks (R-

CNNs), can be used to find repetition and anomalies. This allows analysts to focus on assessing the AI-analyzed results and drawing higher-level conclusions. Moreover, integrated AI techniques can enable more natural interactive exploration. Conversational interaction using NLP and visualization technology can create a more engaging experience, enabling users to engage with AI agents in information architecture spaces. These agents can help to extract important insights from visualization tools. With well-defined analytical objectives and limitations, AI methods can also provide suggestions for analysts' actions, effectively collaborating with human analysts.

7.2.3 AI for parallel user behavior analysis in IA

Leveraging AI capabilities for natural interaction in an information architecture can make tracking user behavior within IA systems easier, opening up opportunities for further analysis of user behavior in these scenarios. Duvivier et al. [31] have identified that evaluating behavioral data exploration and extracting meaningful insights represent a significant challenge. However, a recent review has provided insights for human behavior analysis in simulated virtual worlds [102]. AI-based user behavior analysis has been developed for years. For example, topics such as eye-tracking and emotion estimation have been widely discussed when evaluating AI systems. However, more research is needed to use AI to analyze user behavior in real-world situations, to create personalized AI experiences, and to optimize visualizations automatically. Guidelines and frameworks need to be developed in these areas to allow for the use of multi-modal user behavior data. In addition, using AI models to generate narrative data based on user interaction in real-world situations may help address the shortage of data in the field of AI evaluation. This could lead to new methods of evaluating AI by analyzing user behavioral patterns when interacting with a wide range of AI systems.

7.3 Opportunities in general IA fields

We have also identified four opportunities and future directions in the general IA research domain in terms of data types, research types, application characteristics, and required tools and platforms.

7.3.1 Multimodal and wider data types in IA applications

We note that discussions at the intersection of AI and IA have primarily focused on specific data

types tailored to particular application scenarios. The papers considered have research focuses on various types of data, including 3D geospatial data [41, 46], abstract high-dimensional data [30, 39, 56, 61, 65, 67], visual data (i.e., images, video) [29, 33, 34, 36, 40, 50] and textual data [36]. However, not many studies explore IA for multimodal data analysis and large-volume data with complex structures. For example, Duvivier et al. [31] investigated using user behavioral data (interaction trajectories and events) to understand analytical behaviors in an immersive VR environment. However, there is little discussion of the potential of incorporating multimodal data such as user eye-tracking, locomotion, voice/speech data, and other physiological data such as heart rate and electroencephalography. Moreover, guidelines for using multimodal data to understand user behaviors in IA systems are still in their infancy.

Given that AI techniques are employed for intricate data mining and analysis tasks, we anticipate that exploring a wider array of data types in the context of combining AI and IA holds significant promise. Within the paradigm of IA, a broader range of data types, such as temporal data, spatial-temporal data, graphs, and trees, have been explored [6]. Specifically, IA solutions for complex data analysis involve tasks such as data sharing across multiple platforms and domains, and privacy issues may benefit from decentralized AI techniques like federated learning and swarm learning [103]. While these strategies have not been widely adopted in the current IA community, they could be promising directions to explore.

7.3.2 General frameworks and guidelines for IA design

Our analysis indicates a scarcity of theoretical studies focusing on the intersection of AI and IA; most included studies focus mainly on technical aspects, with empirical studies and implementation studies being the primary study types. This observation stems primarily from the inclusion criteria for this work, which specifically exclude review or survey papers, potentially omitting a notable quantity of theoretical research. Furthermore, given that the convergence of AI and IA represents an emerging field of study, it is plausible to anticipate a delay in the development of theoretical discourse and methodological recommendations of a general kind. Despite these factors, we expect future research to

more substantially engage with both the theoretical foundations and methodological guidelines relevant to this field of investigation. Specifically, problems such as integrating AI techniques into IA workflows in general and how to model AI-supported knowledge generation processes in IA should be resolved in future work.

7.3.3 AI-supported collaborative IA

The analysis results of RQ1 highlighted a limited research focus on collaborative IA research with AI advances. From RQ1, we find that most applications in the included studies targeted multi-user scenarios, while they hardly investigated collaborative IA. For example, applications in *Education/Training* (A1) [32, 49, 58, 63] and *Smart healthcare* (A3) [30, 39, 48, 65] categories present IA systems that allow collaboration between educators and students for learning performance analysis as well as between multiple medical experts, but only a few studies examine collaboration between multiple users for decision-making processes [30, 32]. However, it is worth noting that research efforts have not addressed gaps in collaborative IA applications, as they focus more on IA solutions for use cases where all users collaborate in the same physical space. In this review, no use case of remote collaboration using AI-supported IA systems was found. As collaborative AI incorporates multi-user intelligence, enabling users with different backgrounds to collectively address complex analytical problems, there is a significant research gap in IA.

The current paradigm defines collaborative IA as primarily involving human–human collaboration in either the same physical location or remotely. However, AI can potentially expand the concept of collaborative IA to include human–AI collaboration. For example, AI-based virtual assistants in immersive spaces can facilitate interactive exploration processes and contribute to knowledge generation. Recent research has shown the potential of integrating LLM-based conversational agents in MR applications [104]. Furthermore, our research has revealed that most efforts in AI-supported collaborative IA focus on co-located collaboration scenarios, leaving a gap for research on remote collaborative IA, where technical architecture and resource allocation between multiple users are crucial issues deserving future exploration.

7.3.4 Generalized platforms and toolkits

Even though toolkits and frameworks for specific IA scenarios have emerged in recent years, there is still a lack of IA toolkits with the versatility and capability to support different data types and visualization devices. A persistent legacy is that explicit implementations are still based on mainstream game engines such as Unity and Unreal, and standalone platforms dedicated to IA system development are lacking, which is not conducive to the generalization and extensibility of IA research. Therefore, we advocate that the IA community should provide a dedicated platform or architecture for scalable IA solutions that integrate AI techniques in a standard way and allow customized data visualization types in the future.

It is noticeable how the shared use of traditional 2D displays and 3D displays for IA systems remains a relatively unexplored technical challenge. Although studies have compared user experiences across various devices, such as desktop-based tools, VR HMDs, and AR HMDs, there is still a research gap in this area. The extension from traditional 2D visualization devices to fully immersive visualization spaces is ongoing. Therefore, enabling smooth collaboration between users of traditional 2D visualization devices and immersive visualization devices can help create comprehensive AI systems that address current visualization limitations and improve collaboration between multiple users. Compatibility issues between different software tools and platforms can be challenging at the current stage, while future work may investigate how to adopt open standards and APIs that facilitate interoperability between different systems, which will require collaborative effort between AI developers and VR hardware manufacturers.

8 Discussion

By reviewing research efforts at the intersection of AI and IA domains, our analysis has identified eight application domains varying from conventional XR application scenarios such as education/training, manufacturing, and smart healthcare to emerging areas such as sports events and assistive systems, as shown in Table 4. These identified applications are consistent with most research directions of AI and XR combinations [105–109], while the integration of IA

enables users to gain insights from manipulations in those applications. Most AI techniques involved in IA pipelines are incorporated to support data collection, data mining, and visualization generation, in the same way that AI techniques are typically utilized to support conventional VA tasks [20, 21, 98]. However, although an immersive experience characterizes the unique factor that differentiates IA from conventional VA, our analysis finds that rare studies address AI techniques to enhance the immersive experience in IA systems. Notably, a few studies focus on the use of IA to provide more immersive features to enhance the explainability and interoperability of AI training processes, which has been termed VIS4AI [20, 110]. Despite the development of the IA community for years, this trend reveals a discrepancy between AI–IA integration and AI–VA integration.

Therefore, we envision a higher-level integration of AI and IA as a promising future direction for complex data analysis. More natural interaction techniques should be utilized to enhance the immersive experience, and more advanced AI techniques could be integrated to support decision-making and analytical reasoning processes. From a technical perspective, we have identified several key issues that may impact the design processes and scalability of future AI-supported IA applications.

We acknowledge that various possible factors may impact the reliability of our findings. Firstly, the study targeted a relatively narrow research scope, potentially excluding relevant studies in the immersive visualization field or emerging AI topics. Furthermore, the search strategy was restricted to a few major databases and limited to English-language publications, potentially omitting relevant studies published elsewhere or in other languages. In terms of the data extraction process, information may be indirectly reported or missing in some studies, thus affecting the comprehensiveness of this review. However, despite all identified limitations, the consistencies between our results and other recent reviews may go some way to indicating the reliability of this study.

9 Conclusions

With an aim of capturing the state-of-the-art of integration of AI techniques into the IA field, this systematic literature review has explored three stated

RQs: (i) what are the significant application domains of AI–IA integration, (ii) what AI techniques have been utilized and how were they combined, and (iii) what are current challenges and future directions? Based on a systematic search, we gathered a corpus of 43 relevant studies. Our findings indicate that the combination of AI and IA research fields is still in its early stages. The integration of AI and IA has proved significant in the fields of manufacturing, smart healthcare, and education/training. Moreover, AI–IA integration has been explored in emerging applications in other professional disciplines where AI and XR have been investigated separately, such as assistive systems, urban planning, disaster management, and sports events. Additionally, using AI to enhance IA theoretical or technical research has been a significant research direction, following an early research direction of AI4VIS. On the other hand, using IA to enhance XAI and support human–AI interaction has also been a significant research direction. In terms of AI–IA integration, we extended the conventional VA pipeline into an AI-supported IA pipeline by identifying five dimensions of AI support. Among all these combinations, AI techniques contributed mainly to data mining and visualization generation phases. Furthermore, we found that existing research efforts have focused on a limited scope of data types and research topics.

This paper has delivered our contributions from three perspectives: firstly, it presented an overview of prior research into AI–IA integration, from application scenarios to technical advancements. Secondly, it provided an updated pipeline that can be applied to general IA applications with integrated AI techniques. Moreover, it identified four challenges and seven opportunities for future exploration, which may provide insights for researchers and practitioners in this field to propose novel methods and application scenarios.

Appendix

Complete list of publication venues with abbreviations

ISMAR: IEEE International Symposium On Mixed And Augmented Reality
IEEE AIVR: IEEE International Conference On Artificial Intelligence And Virtual Reality
IEEE TVCG: IEEE Transactions On Visualization And Computer Graphics

ACM CHI: CHI Conference on Human Factors in Computing Systems
ACM ISS: ACM International Conference On Interactive Surfaces And Spaces
IEEE VR: IEEE Conference On Virtual Reality And 3D User Interfaces
ADIPEC: Abu Dhabi International Petroleum Exhibition And Conference Adip 2021
CIDR: Biennial Conference on Innovative Data Systems Research
CISTI: Iberian Conference On Information Systems And Technologies
eCAADe: Education and Research in Computer Aided Architectural Design in Europe
IEEE GCAT: Global Conference for Advancement in Technology
IEEE ICIMIA: IEEE International Conference on Innovative Mechanisms for Industry Applications
ICMCIS: International Conference on Military Communication and Information Systems
ACM IMX: ACM International Conference On Interactive Media Experiences
IEEE SMC: IEEE International Conference on Systems, Man, and Cybernetics
VARE: International Conference of the Virtual and Augmented Reality in Education
VRST: Proceedings Of The ACM Symposium On Virtual Reality Software And Technology
EuroVis: Eurographics Conference on Visualization
Applied Sciences: Applied Sciences (Switzerland)
PACM HCI: Proceedings of the ACM on Human–Computer Interaction
Applied Spectroscopy: Applied Spectroscopy
CMPB: Computer Methods And Programs In Biomedicine
FAIA: Frontiers In Artificial Intelligence And Applications
Future Internet: Future Internet
IEEE Systems Journal: IEEE Systems Journal
MFGLET: Manufacturing Letters
Scientific Reports: Scientific Reports
Sensors: Sensors (Switzerland)
Virtual Reality: Virtual Reality
EuroVA: International Workshop on Visual Analytics (EuroVA)
MLUI: IEEE Workshop On Machine Learning From User Interaction For Visualization And Analytics
iCity: iCity. Transformative Research for the Livable, Intelligent, and Sustainable City



Author contributions

Chaoming Wang: Conceptualization (lead), Literature Search, Methodology (lead), Formal Analysis, Validation (equal), Writing—Original Draft, Writing—Review Editing (equal). Valeria Garro: Conceptualization (supporting), Validation (equal), Writing—Review Editing (equal). Veronica Sundstedt: Funding Acquisition, Validation (equal), Writing—Review Editing (equal). Yan Hu: Methodology (supporting), Validation (equal), Writing—Review Editing (equal). Prashant Goswami: Validation (equal), Writing—Review Editing (equal).

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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