Journal of Cases on Information Technology
Volume 25 • Issue 1

Answering Why and When?
A Systematic Literature Review of Application Scenarios and Evaluation for Immersive Data Visualization Analytics

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ABSTRACT

Immersive analytics (IA) is a fast-growing research field that concerns improving and facilitating human sense making and data understanding through an immersive experience. Understanding the suitable application scenario that will benefit from IA enables a shift towards developing effective and meaningful applications. This paper aims to explore tasks and scenarios that can benefit from IA by conducting a systematic review of existing studies and mapping them according to the multi-level typology for abstract visualization tasks, which is also known as the what-why-how framework. The study synthesizes several works to answer the why within the context of multiple levels of specificity. In addition, this study also explores the application domains and IA guiding scenarios to address when scenarios best integrate with IA. Then, the paper discusses the IA evaluation types and research methods to evaluate an IA application that can promote effective user engagement in IA. Finally, the limitations and potential future works are discussed.

KEYWORDS

Data Visualization, Immersive Analytics, Mixed Reality, Systematic Literature Review, Task and Requirements Analysis, Virtual Reality, Visual Analytics

DOI: 10.4018/JCIT.323799

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INTRODUCTION

The emergence of big data marked the beginning of a new era of data visualization, leading to a significant evolution of visual analytics over the past several decades. As the volume and intricacy of data rise, the importance of improved data visualization tools also increases. In response to this demand, new data visualization market leaders have emerged, including Tableau, Spotfire, and QlikView. These companies provide sophisticated features and capabilities that enable users to visualize and interact with data in novel manners. Established corporations like Microsoft, IBM, and Oracle are also major players in the data analytics industry. Microsoft offers PowerPivot for data modeling and analysis. It later released Power View, a data visualization tool that allows for the creation of interactive visualizations. IBM provides Cognos Insight, a data visualization product that enables the creation of dynamic dashboards and reports with tools for exploration, analysis, and visualization. Moreover, Oracle acquired Endeca, a data discovery and visualization company. The organization integrated its technology into its business intelligence and analytics solutions, allowing users to explore and analyze data using interactive dashboards and reports. Over the years, existing software has also evolved to incorporate new features and functionality that reflect the changing requirements of consumers in this era of big data.

The use of immersive technologies, namely virtual reality (VR), augmented reality (AR), and mixed reality (MR), have gained widespread notoriety and acceptance. Furthermore, their usage extends beyond the gaming and entertainment industries. Immersive applications have been commonly used in fields like geographic information systems (GIS), healthcare, engineering, data analytics, and visualizations. As the need for enhanced data visualization tools grows more prevalent, immersive technologies usage in data analytics has evolved into a field known as immersive analytics (IA). This new approach to data analysis relies on VR, AR, and MR technologies to create an immersive environment for exploring and analyzing complex data. By allowing users to visualize and interact with data in three dimensions (3D), IA promotes user engagement with data in a more natural and intuitive way. Users within an IA environment can perform real-time data exploration and manipulation by moving around and interacting with 3D visualizations in a virtual space, thus making it easier to analyze and navigate large datasets and gaining better insights into data through a user-friendly, immersive data interaction. This approach is particularly useful for processing and visualizing complex datasets, such as those typically found in scientific research, engineering, healthcare, industry, business, and other domains.

Although IA is still in its infancy, the use of these technologies in data visualization has been proposed since the early 1990s (Fonnet & Prie, 2021). Representing and displaying 3D data in an immersive environment offers better insight and enhances human perception. Furthermore, this type of data representation could be an enhanced alternative to some limitations in conventional two-dimensional (2D) data representation. Promising opportunities have sparked the interest of researchers from fields like data visualization, VR, human-computer interaction (HCI), and computer graphics into the field of IA to improve the understanding of data through immersive features. As a result, the use of immersive technologies in visualization tasks has exploded into a growing field of research.

While many studies have demonstrated the advantages of IA in different domains, several challenges in delivering practical and effective IA applications are still present (Ens et al., 2021). One of the main challenges is identifying suitable application scenarios for IA. From this perspective, answering the questions of *why* (*Why is IA used to perform this task?*) and *when* (*When is the best scenario to integrate IA?*) should be addressed. Therefore, this article aims to explore the scenarios and tasks in IA applications by conducting a systematic literature review to collect related studies. This review targets to answer three research questions and their objectives (see Table 1). The authors analyzed and mapped the user tasks in IA applications from a list of works based on the *what-why-how* design framework (Brehmer & Munzner, 2013) by focusing on the *why* section of the framework. Then, the authors extracted and classified the application domains and IA guiding scenarios to

Table 1. Research questions and research objectives

Research Questions (RQs)	Research Objectives (ROs)
RQ1: Why is the IA application used to perform analytical tasks?	RO1: To explore the multi-level analytical tasks provided by IA applications
RQ2: When is the best-case or worst-case analytical scenario to integrate IA application?	RO2: To investigate the application domains and guiding scenarios of IA applications
RQ3: What is the most effective way to evaluate the performance of IA applications?	RO3: To associate the IA value assessments and research methods to provide recommendations and guidelines to facilitate IA application creation and evaluation

investigate the best- and worst-case scenarios in IA applications. Lastly, IA evaluation types and research methods were systematically mapped to present recommendations for users or developers to create an IA application that promotes effective user engagement in IA.

This article is organized as follows. The following sections discuss the literature review, methodology, and results obtained from the systematic mapping. Then, the article explores the limitation and bias risks to caution future studies and provide suggestions for improvement. Finally, the conclusion section summarizes this work.

RELATED WORKS

The organization of Brehmer and Munzner's typology (2013) centered on distinguishing *why* a task is performed, *how* a task is performed, and *what* they pertain to. Their research claimed that most of the existing classification systems were unable to solve ends-means confusion, such that the low-level system only answered *how* a task is performed whereas the high-level ones only addressed *why* a task is performed. Therefore, they aimed to close the gap by providing a multi-level description of visualization tasks to solve the ends-means confusion while facilitating user reasoning and communication of tasks. Subsequently, Marriott et al. (2018) studied the previous *what-why-how* framework and came up with an extension of the work called the *where-what-who-why-how* framework. They included two additional elements: *Who* are the users? *Where* is the system to be used? The framework was created with the purpose of providing a comprehensive multidimensional organization for designing IA applications and comprehending research in the field.

Being a new field of research, the discussion on IA comprised a wide range of topics, including the research challenges in the field as presented by Ens et al. (2021). In this article, 17 grand challenges have been compiled concerning four topics in IA. Identifying suitable application scenarios in IA has been identified as one of the challenges. It pivoted toward answering the *why* (Why do specific scenarios benefit from IA while others do not?) and the *when* (When in the overall analytics workflow can we best integrate IA?). As a matter of fact, providing answers to these questions is the primary motivation of this article.

An existing work by Fonnet and Prie (2021) presented a comprehensive survey on IA applications with a broad topic of discussion on technologies, sensory mapping, and interaction techniques from 30 years ago. In this article, the interaction techniques are discussed and mapped based on task by type taxonomy (TTT) by Shneiderman (1996). Additionally, a more recent work by Siang et al. (2021) implemented TTT in their systematic literature review on information exploration tasks in IA. These works have extensively addressed the *how* in the multi-level typology; therefore, this article focuses on discussing the *why* and *when* within the scope of the framework.

Furthermore, Kraus et al. (2021) proposed four guiding scenarios to demonstrate the effective utility of IA application: (1) situated visualization; (2) spatial analysis with spatial tasks; (3) collaboration; and (4) presentation. They also discussed the importance of evaluating the IA application to show the benefits and drawbacks of IA. Three IA value assessment types can be employed to assess the IA application: (1) examples or demonstration; (2) property evaluation across different media; and (3) comparisons between immersive and non-immersive scenarios. Although their work only focused on the overview of research areas, it provided opportunities and challenges for future studies in IA application, particularly in answering *when* the IA showed promising solutions and *what* are the recommendations to evaluate the IA application.

METHODOLOGY

The study follows the systematic literature review methodology based on the evidence-based software engineering (EBSE) approach by Kitchenham et al. (2007) integrated with McNabb and Laramee (2019) data extraction and systematic mapping strategy. It is made up of the searching stage and analytical stage.

Searching Stage

Before conducting the search, the PICO criteria have been determined as presented in Table 2. The criteria have been identified to establish the scope of the study, define the search strings to be used, and assist the screening process of relevant studies. Then, the phase continues by identifying the databases or libraries to be used in the literature search and collection. The databases involved were IEEE Xplore and Association for Computer Machinery (ACM) Digital Library.

The search strings used the following keywords: “virtual reality,” “mixed reality,” and “immersive analytics.” The AND operator is used to combine those keywords with “data analy*” and “data visual*.” In addition, the authors utilized the NEAR operator within five letters between “data” and “analy*” or “data” and “visual*” (if available in the database advanced search). Therefore, the search keywords are more diversified. They may include “data analysis,” “analyzing data,” and “analysis of data.” They may return more focused and accurate search results. Besides, the wildcard “*” was used to retrieve higher relevance records, in which “visual*” can be extended to “visualizing,” “visualizer,” or “visualization.” The goal of this study was to find relevant works about IA applications; therefore, the AND operator was used to add the keyword “application” to the search string. The search process was done using the databases’ advanced search features and searched within the abstract or title or keywords. Furthermore, the search was set to include conference proceedings, journal articles, and review papers within 10 years (2012–2022).

Table 2. PICO criteria of the study

(P) Population – Target group for the investigation	• Immersive analytics (IA) software application, emphasizing virtual reality and mixed reality (IA) technologies
(I) Intervention – Investigation aspects or issues of interest to the researcher	• Application scenarios or tasks involving data visual analytics
(C) Comparison – Aspect of the investigation with which the intervention is being compared	• Between visual encodings and user interactions • Between different devices or media • Between immersion and non-immersion
(O) Outcome – Effect of the intervention	• Expound on the examples or demonstration, use cases, and case studies. • Evaluate properties of IA based on performance, usability, or comparison between different interactions. • Evaluate values of immersive based on different devices or media and immersion versus non-immersion.

Analytical Stage

This phase focuses on analyzing and synthesizing the selected works gathered from the previous stage. The first level of the screening process involved a brief reading of the literature to identify the works that fulfilled the inclusion criteria of this study. This was done by reading four sections of the article (i.e., title, abstract, introduction, and conclusion). The inclusion criteria are presented as follows:

- The work must have at least one author and title.
- The topic is related to IA or data visualization analytics using immersive technologies (VR/MR).
- The content must include the goals and objectives of the application or technology or proof-of-concept and the tasks or scenarios in which those were implemented.
- The article must be in the English language.

Literature works that failed to match any of the criteria were excluded. Additionally, any duplicate works were omitted from the list. For articles with follow-up research, the authors read the goals and purposes of these articles and chose the article with the most goals if they are similar.

Then, the quality of the remaining works was assessed through full-text analysis. As shown in Table 3, the main constructs of the assessment were design, conclusion, conduct, and analysis (Kitchenham et al., 2007). The complete questionnaire for quality assessment can be found in Supplementary Data A. The two types of measurement scales focused on selecting one of the criteria scores and cumulating the criteria scores. For the first measurement scale type, different scores were assigned to each selection criterion and the authors chose the criteria that were suitable. Meanwhile, the second measurement scale type provided several selections for the authors to choose either one selection, more than one selection, all selections, or none to accumulate the scores that were assigned to each criterion. Only the conduct and analysis questions have a total score of two because some articles implemented mixed-method research that included both qualitative and quantitative studies. The total score was seven. Only the articles that scored greater than three were accepted for the next stage.

The next part of this phase was selecting the most relevant articles by performing a full-text review on the filtered list of works. The list was refined by extracting several elements from the papers adapted from McNabb and Laramee (2019) as follows:

- **Concept:** Aim, research goal, and article's contribution.
- **System Implementation:** Development of IA application to physically realize the concept, including theoretical framework, visualization techniques, hardware and software requirements, and dataset used.

Table 3. Quality assessment questions

Construct	Questions	Measurement Scale Types	Total Scores
Design & Conclusion	Are the aims, research objectives, or research questions clearly stated and achieved or answered?	Select one	1
Design 1	Is the visualization technology (IA) or method clearly defined? For example, the name of the technique, algorithms, and step-by-step description.	Select one	1
Design 2	Type of research design.	Select one	1
Conduct	Was the implementation of the experiment conducted appropriately? Including **qualitative** and **quantitative**.	Cumulate scores	2
Analysis	Was the result of the experiment evaluated appropriately? Including **qualitative** and **quantitative**.	Select one or cumulate scores	2

- **End Goal or Benefit for User/Domain:** Target solution provided by the IA application and its evaluation results.
- **Application Domain:** Professional domain used in the IA application study, such as physics, GIS, or astronomy.
- **Application Scenario/Test Case/User Study:** Experiment conducted to investigate the effectiveness of the IA application, including evaluation tasks, metrics, participants, and instruments used (the authors also classified each study with the evaluation types as listed in the Outcome (O) of PICO and suitable guiding scenario according to Kraus et al., 2021).

Finally, the selected papers were mapped based on the multi-level typology of abstract visualization tasks, focusing only on the *why* of the design framework. Besides that, the application domains and guiding scenarios were synthesized to explore the application scenarios to answer the *when*. Lastly, the authors classified the IA value assessment methods and associated them with the research methods and instruments employed by previous studies. The results of the data collection, analysis, and systematic mapping are reported in the next section.

RESULTS

Search Results

The initial search process returned a total of 197 records, with 149 from IEEE Xplore and 48 from the ACM Digital Library databases. Both are comprehensive databases with a rich collection of articles covering computing and information technology. This includes conference proceedings, journal articles, and more. Next, the authors removed duplicate records, leaving 139 articles for the screening stage. There were 54 records remaining after applying the inclusion criteria. Then, the authors conducted a quality assessment and obtained 25 articles for full-text reading and data extraction. The extracted data were analyzed and synthesized as elaborated in the Results section. Figure 1 depicts the overview of the selection process.

Quality Assessment Result

The quality assessment was conducted on 54 records obtained after applying the inclusion criteria and removing duplicates. These works were graded on four parts: (1) design; (2) conclusion; (3) the way the work was done; and (4) the way it was analyzed. The conduct and analysis constructs comprised quantitative and qualitative evaluations, each counting for one point. Table 4 shows the quality assessment results.

Out of the 54 studies, 29 were excluded for scoring less than three points in the assessment. Meanwhile, 25 studies with a range score of three to seven were selected to be analyzed and synthesized. These selected works were classified into three categories: (1) less than four points; (2) four to five points; and (3) six to seven points.

In the first category (less than four points), seven articles were included from 2015 to 2021. These all scored one point each for the conclusion and either one point or one-half point for the design. The selected works in this category lost most of the points for mentioning only the qualitative or quantitative method or none in the conduct and analysis section. Additionally, most of the studies were conducted in the domain of GIS, followed by general usage and healthcare.

Apart from that, 10 works were found in the second category (four to five points), with all scoring full points for the first two sections. These studies included either qualitative or quantitative evaluations or both for the conduct and analysis parts, which contributed one point or at least 0.4 points. The list of works consisted of conference papers from 2014 until 2022 from various domains, including GIS, industrial engineering, automotive, healthcare, software engineering, and general purpose.

Figure 1. Selection process flowchart

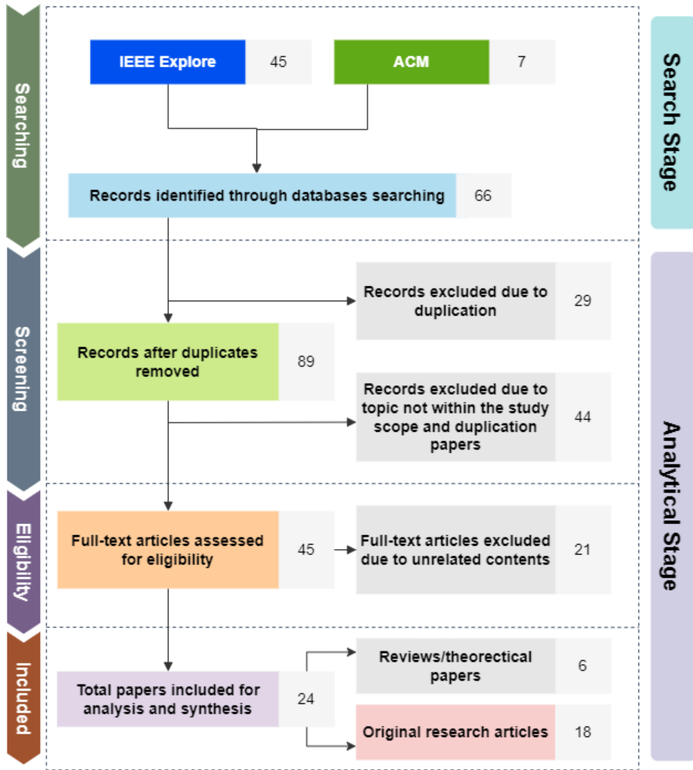


Figure 2. Number of selected articles vs. year

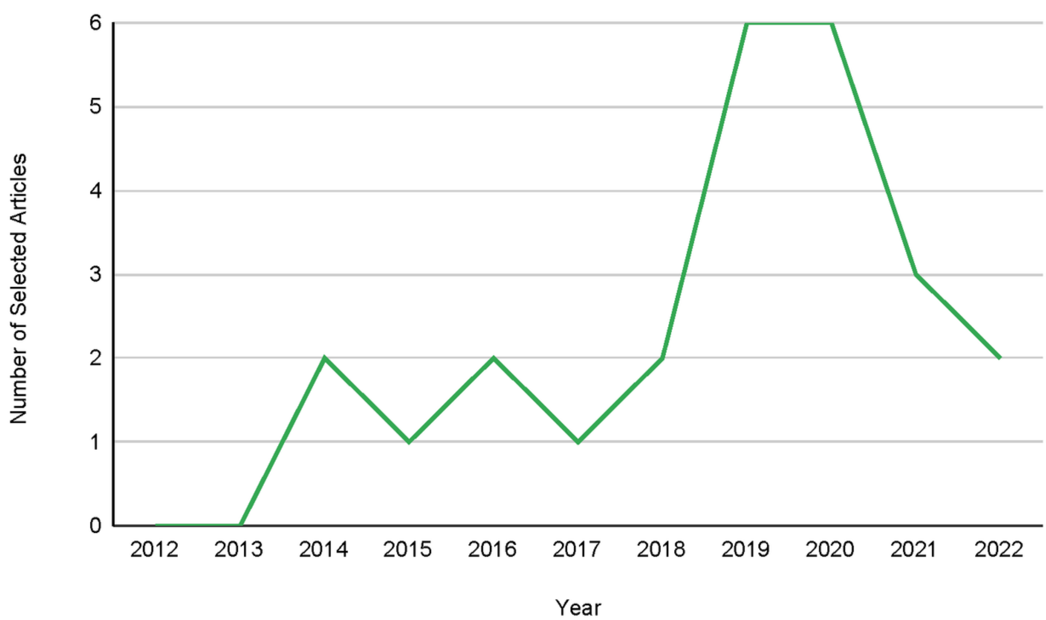


Table 4. Quality assessment results

IA Application / System	Quality Assessment Criteria								Google Scholar Citation (as of 8th January 2023)	Application Domain
	Design & Conclusion	Design 1	Design 2	Conduct - Quantitative	Conduct - Qualitative	Analysis - Quantitative	Analysis - Qualitative	Assessment Scores (/7)		
3D visualization of borehole data based on WebGL and VR (Ma et al., 2021)	1	1	0.5	0	0	0	0.5	**3**	17	GIS – Environmental Science
CAVE immersive VR system with 3D GIS (Chen et al., 2020)	1	1	0.5	0	0	0	0.5	**3**	0	GIS – Smart City and Urban Planning
GraphVR (Capece et al., 2018)	1	1	0.5	0	0	0	0.5	**3**	0	General purpose
Natural environments visualization from data in VR (Huang et al., 2019)	1	1	0.5	0	0.2	0	0.5	**3.2**	7	GIS – Environmental Science
Tangible Braille Plot (Walsh et al., 2018)	1	1	0.5	0	0.2	0	0.5	**3.2**	10	GIS – Others
Multi-projection visualization system using VR and mobile devices (Neto et al., 2015)	1	0.5	0.5	0	0.6	0	0.75	**3.35**	1	CS – Information Management
Visualization and interaction with MRI scans in VR (Cecotti et al., 2020)	1	1	0.5	0.5	0	0.5	0	**3.5**	3	Healthcare – Medical Imaging
WaveCharts (Kloiber et al., 2020)	1	1	1	0	0.4	0	0.75	**4.15**	0	Engineering – Industrial Science
3D city data visualizationwa and viewer behavior analysis in VR (Sun et al., 2020)	1	1	1	0.6	0	0.75	0	**4.35**	1	GIS – Smart City and Urban Planning
Interdisciplinary IA at the Electronic Visualization Lab (Marai et al., 2017)	1	1	1	0	0.8	0	0.75	**4.55**	29	GIS – Environmental Science; Astronomy, Healthcare – Medical Imaging
KratosVR (Oliveira et al., 2021)	1	1	1	1	0	0.75	0	**4.75**	0	Engineering – Automotive
VR environment for engineering design review (Wolfartsberger et al., 2017)	1	1	1	0	0.8	0	1	**4.8**	35	Engineering – Industrial engineering
ExplorViz (Krause-Glau & Hasselbring, 2022)	1	1	1	1	0	1	0	**5**	3	CS – Software Engineering
Graph data visualization of news using VR (Pachas-Banos et al., 2019)	1	1	1	1	0	1	0	**5**	25	General purpose

continued on following page

Table 4. Continued

IA Application / System	Quality Assessment Criteria								Google Scholar Citation (as of 8th January 2023)	Application Domain
	Design & Conclusion	Design 1	Design 2	Conduct - Quantitative	Conduct - Qualitative	Analysis - Quantitative	Analysis - Qualitative	Assessment Scores (/7)		
Data annotation workflows evaluation for CAVE-like virtual environments (Pick et al., 2016)	1	1	1	1	0	1	0	**5**	1	Architecture – Design Review
Effectiveness of VR and gesture control to visualize complex weather data (Andersen et al., 2019)	1	1	1	1	0	1	0	**5**	14	GIS – Environmental Science
VR prototype to aid visualization of gait analysis (Alfalah et al., 2014)	1	1	1	1	0	1	0	**5**	0	Healthcare – Musculoskeletal
Comparison of environments for archaeological exploration of 3D landscape data (Bennett et al., 2015)	1	1	1	1	0.8	0.5	0.7	**6**	30	GIS – Others
Visual comparison of networks in VR (Joos et al., 2022)	1	1	1	1	0.8	1	0.5	**6.3**	0	Healthcare – Medical Imaging
IATK (Immersive Analytics Toolkit) (Cordeil & Dwyer, 2019)	1	1	1	1	0.8	1	0.9	**6.7**	92	General purpose
Visualization of real-time heterogeneous smart city data using VR (Broucke & Deligiannis, 2019)	1	1	1	1	1	1	0.75	**6.75**	7	GIS – Smart City and Urban Planning
Hybrid analytics system for collaborative exploratory data analysis (Cavallo et al., 2019)	1	1	1	1	1	1	1	**7**	44	General purpose; Healthcare – Health Informatics
Hybrid asymmetric collaborative immersive analytics system (Reski, Alissandrakis, & Kerren, 2020)	1	1	1	1	1	1	1	**7**	10	GIS – Social Media Analysis
Exploration of time-oriented data in immersive VR (Reski, Alissandrakis, Tyrkkö, et al., 2020)	1	1	1	1	1	1	1	**7**	5	GIS – Social Media Analysis
CodeCity (Moreno-Lumbreras et al., 2021)	1	1	1	1	1	1	1	**7**	5	CS – Software Engineering

The remaining works comprised eight articles from 2014 to 2021. They were classified in the last category (six to seven points). Three works scored the full points, whereas the rest scored at least one-half of a point for the last two sections of the assessment. The domain for these studies was mostly identified for general purposes, followed by GIS and software engineering. Furthermore, all these works were cited at least 5 times (at most 92 times) based on Google Scholar citations.

Research Trend

Next, the authors investigated the research trend of IA application in terms of the year. Table 5 shows the number of selected publications by year. Both 2019 and 2020 achieve the highest number of research records, with six studies for each year. Meanwhile, 2015 and 2017 have only one related study, respectively.

The result shows a decreasing trend from 2021 to 2022. There are several reasons for this phenomenon. First, although there are only three studies selected from 2021, there are numerous VR-related applications published that are not limited to IA studies, including VR in simulation systems and education. As seen in Table 4, the total number of VR-related publications during the screening stage increases to 26 studies in 2021 compared to 21 studies in 2020. Second, the authors filtered out the AR technology for IA applications because the scope of this research focuses on VR and immersive technologies. In the future, AR technology should be included in the study for the benefits of IA application development.

RQ1: Systematic Mapping Using Multi-Level Typology of Visualization Task

The *why* section of the multi-level typology of abstract visualization tasks consisted of high-level (consume and produce), mid-level (search), and low-level (query) tasks. The consume tasks referred to the use of visualization to consume information in various domain contexts, including the need to *present* information, to *discover* or analyze new information, and to *enjoy* the visualization through casual interest or curiosity. *Produce* tasks involve the creation of new information, which can be accomplished through *annotating, recording,* or *deriving.* At the mid-level, the elements of interest were looked for by using the tasks *lookup* (target known, location known), *locate* (target known, location unknown), *browse* (target unknown, location known), and *explore* (target unknown, location unknown). Furthermore, the query tasks at the low level were presented in accordance with the number of search targets, in which *identify* refers to a single target, *compare* is used for multiple targets, and *summarize* provides an overview of the data. Additionally, the authors included the *share* task at this level to refer to collaboration activities.

While this typology was designed to describe *why* a task is performed, the authors considered that it could also be adapted to describe *why* the application is used to perform the task. Diaper and Sanger (2006), in defining the concept of HCI tasks, suggested that there is a strong relationship between goals and tasks in a *work* system of an HCI application. The *work* system is defined as a system composed of one or more people, the direct end user or operator, and at least one computer system. It is also in charge of carrying out tasks to achieve the goals that it possesses.

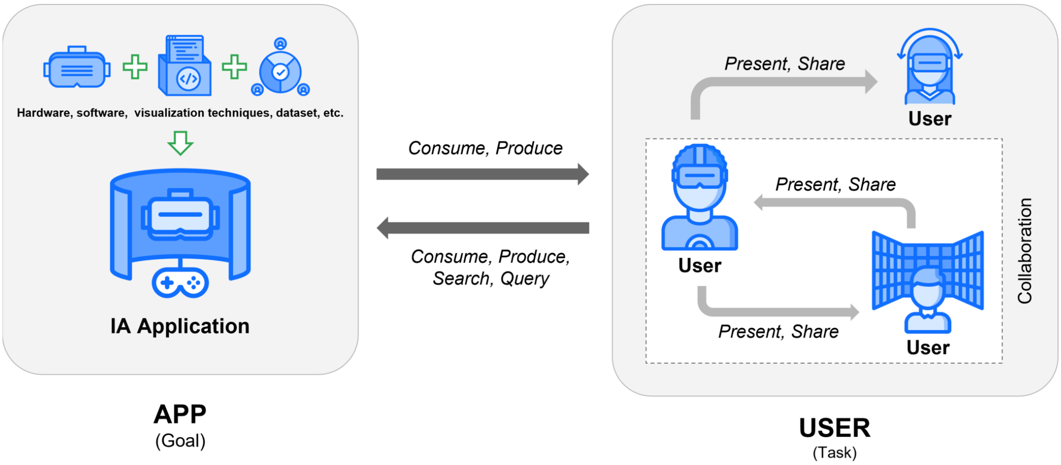
This article adapts the multi-level typology to present a system mapping that addresses the first research question of this article from the application and user perspectives. Figure 3 shows an overview of the adapted typology based on the idea of goals and tasks.

To define the goal of the IA application, the authors investigate the following question: *Why is visualization used in the immersive environment or with immersive technology?* The authors argue

Table 5. Number of publications by year

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
Number of Selected Articles	0	0	2	1	2	1	2	6	6	3	2	25
Total Articles During Screening Stage	6	5	7	3	8	9	9	22	21	26	23	139

Figure 3. Overview adapted typology based on goals and tasks



that the high-level tasks in multi-level typology (*present*, *discover*, *enjoy*, and *produce*) are sufficient to answer this question. The searching and querying tasks are mostly user-dependent; hence, the mid-level and low-level tasks are not considered to answer the question. In addition, the question, *Why does a task take place in an immersive environment or use immersive technology?*, is addressed in the user context to explain *why* the tasks were done in the IA application. Table 6 summarizes the mapping result based on the 25 selected studies.

Answering: Why Is Visualization Used?

Based on the mapping results, most of the studies were mapped to *present* (18 works), *discover* (6 works), and *produce* (1 work) tasks. Arguably, no study was identified to use *enjoy* as its high-level task. They were all identified to have a defined goal of using visualization in the IA system. This implied that the tasks carried out were not simply for casual interaction or curiosity.

The use of visualization to *present* information on geographical 3D data in a virtual environment was identified through the work of Ma et al. (2021) and Chen et al. (2020). Additionally, the *present* task refers to the use of visualization to communicate information that can improve data understanding and decision making in domains like as GIS (Huang et al., 2019; Reski, Alissandrakis, & Kerren, 2020), information management (Neto et al., 2015), healthcare (Alfalah et al., 2014; Cecotti et al., 2020), engineering (Oliveira et al., 2021; Wolfartsberger et al., 2017) and other purposes (Bennett et al., 2015; Pachas-Banos et al., 2019). Furthermore, Moreno-Lumbreras et al. (2021) and Broucke and Deligiannis (2019) presented an interactive VR application to interact with smart city data. Apart from head-mounted display (HMD) and 3D virtual environments, the CAVE-like system was implemented in some applications to carry out immersive analytics tasks like visualizing MRI and cosmology data (Marai et al., 2017) and data annotation workflow evaluation (Pick et al., 2016). Lastly, the use of collaborative features to support data visualization tasks was discussed through ExplorViz (Krause-Glau & Hasselbring, 2022) and hybrid IA systems (Cavallo et al., 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020).

Cordeil et al. (2019) developed an interactive authoring toolkit, the immersive analytics toolkit (IATK), for data exploration in an immersive environment. This tool allows the creation of 3D graphs, including scatterplots and bar graphs. It was mapped as the *produce* task. In addition, this framework considered *discover* tasks to be associated with generating or verifying the hypothesis of scientific inquiry. The WaveCharts application (Kloiber et al., 2020) implemented VR technology to facilitate anomaly detection. The GraphVR (Capece et al., 2018) offered an intuitive and natural

Table 6. Systematic mapping using what-why-how framework to focus on the why portion of the framework and answer: Why is visualization used? (goals of applications) and why is a task performed? (tasks of users)

References	Goals (Application)	Tasks (Users)	Evaluation Types
3D visualization of borehole data based on WebGL and VR (Ma et al., 2021)	*Present* – communication of information through 3D visualization of geological borehole data.	Not stated.	Examples or demonstration
CAVE immersive VR system with 3D GIS (Chen et al., 2020)	*Present* – guide users to understand 3D GIS data and present spatial knowledge more effectively using the CAVE system.	Not stated.	Examples or demonstration
GraphVR (Capece et al., 2018)	*Discover* – offers a VR tool with a natural and intuitive level of interaction that allows users to explore 3D graphs.	*Produce* – create clusters through the selection of multiple nodes. *Enjoy/Explore* – freely explore and interact with the 3D visualization. *Explore* – move inside the graph and go through all the nodes. *Identify* – visualize details about a node by using the trigger button.	Examples or demonstration
Natural environments visualization from data in VR (Huang et al., 2019)	*Present* – support decision-making and scientific communication through a complex and realistic VR environment with extended IA functionalities.	*Discover* – answer some questions about the general validity of the authors' approach to 3D forest visualization and 3D/VR uncertainty visualization. *Explore* – move through the forest using teleportation. *Compare* – look at a forest in different model inputs and output scenes through slide-and-show functionality.	Examples or demonstration
Tangible Braille Plot (Walsh et al., 2018)	*Discover* – provide interactive means of exploring data through the novel Tangible User Interface (TUI) in a VR environment.	*Summarize* – provides the overview of the entire dataset at start-up and allows zooming out to show all data; identify the data set density and characteristics.	Examples or demonstration
Multi-projection visualization system using VR and mobile devices (Neto et al., 2015)	*Present* – provide means for a better data understanding (immersion and interaction) of 3D graphs representation of relational databases through MiniCAVE and mobile devices.	*Discover* – validate the system using a defined use case. *Explore* – selection feedback acting as a visual reference for navigation within the graph nodes. *Summarize* – provide an overview of 3D graphs through a wide field of view and passive stereoscopy in MiniCAVE.	Examples or demonstration
Visualization and interaction with MRI scans in VR (Cecotti et al., 2020)	*Present* – visualization supports the ability to retrieve and analyze information for researchers and neuroscientists and as an immersive learning tool for teaching neuroanatomy.	*Produce* – select points of interest and edit the points. *Explore/Summarize* – look at the MRI by rotating the head cube with the desired orientation.	Examples or demonstration
WaveCharts (Kloiber et al., 2020)	*Discover* – explore VR capabilities to perform anomaly detection in sensor data of repeated cycles of measurement.	*Produce* – save findings by creating a saved view of the currently displayed data. *Discover* – generate hypotheses about the testers' changing conditions based on data and domain expertise. *Explore/Compare* – explore visualization to compare the peaks of all axes at a point. *Lookup /Identify/Overview* – users can identify sensors and cycles with unusual anomalies by looking at the overview of anomalies per sensor.	Examples or demonstration
3D city data visualization and viewer behavior analysis in VR (Sun et al., 2020)	*Discover* – propose a novel urban data visualization framework and 3D visual variables model in a VR environment.	*Discover* – verify the proposed model's effectiveness and explore the influence of different visual variables on user visual significance. *Explore* – users were allowed to walk and look around in the 3D environment.	Evaluating properties of IA

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Table 6. Continued

References	Goals (Application)	Tasks (Users)	Evaluation Types
Interdisciplinary IA at the Electronic Visualization Lab (Marai et al., 2017)	*Present* – the use of the CAVE2 system to answer questions about data that had been collected and processed and visualize MRI and cosmology data.	*Discover* – evaluate the overall application's usefulness (Dark Sky case study). *Enjoy/Explore* - the user can freely move through the environment and zoom in on a desired halo formation (Dark Sky case study). *Share* – interactive session to share data to come up with answers (Endurance case study).	Examples or demonstration
KratosVR (Oliveira et al., 2021)	*Present* – facilitate the communication of autonomous driving or advanced driving assist systems data through visualization using VR techniques, display information about a certain autonomous driving sequence, and methods of user interaction.	*Discover* – select points of interest and edit the points. *Explore/Identify* – select the data sequence to visualize and interact from the set of available sequences. *Summarize* – see the overview information about the vehicles on the screen.	Examples or demonstration
VR environment for engineering design review (Wolfartsberger et al., 2017)	*Present* – guide engineering design review process through a low-cost multimodal VR-supported tool.	*Produce* – dividing and joining construction groups, based on the CAD modeling structure. *Explore* – use teleportation for traversing in the VR environments.	Evaluating properties of IA
ExplorViz (Krause-Glau & Hasselbring, 2022)	*Present* – presented an approach for a collaboratively usable online software visualization service for program comprehension.	*Produce* – formation of a user-owned software landscape to visualize multiple applications in a single software visualization. *Explore/Share* – shared or collaboratively explored at any time with other users.	Examples or demonstration
Graph data visualization of news using VR (Pachas-Banos et al., 2019)	*Present* – maximize user understanding of the reference between news using graphs using VR technology.	*Discover* – validate the effectiveness of VR in the understanding of the text and relationships shown through graphs. *Lookup/Locate/Browse/Explore* – searching to answer questions given. *Identify/Compare* – querying to answer questions given.	Evaluating properties of IA
Data annotation workflows evaluation for CAVE-like virtual environments (Pick et al., 2016)	*Present* – presented an approach to data annotation workflow design for CAVE-like virtual environment.	*Produce/Lookup/Locate/Identify* – capture information on interesting features, mark it on a screenshot and label it.	Evaluating properties of IA
Effectiveness of VR and gesture control to visualize complex weather data (Andersen et al., 2019)	*Discover* – investigate the effectiveness and usability of different systems using VR and gesture control to visualize complex weather data.	*Present* – users need to visualize data, often using multiple meshes. *Lookup/Locate/Browse/Explore* – find the location of specific points of interest. *Identify* – tasks involved identifying points of interest in the weather visualization.	Evaluating properties of IA, comparative study of immersion versus non-immersion
VR prototype to aid visualization of gait analysis (Alfalah et al., 2014)	*Present* – visualizing motion-captured data for gait analysis in a virtual environment with improved viewing accessibility.	*Discover* – address research hypotheses proposed in the work. *Explore/Compare* – control the speed (low, normal, intermediate, fast) of the moving model to enable the viewer to compare the patient's walk at different speeds.	Evaluating properties of IA
Comparison of environments for archaeological exploration of 3D landscape data (Bennett et al., 2015)	*Present* – provide information in understanding user interaction and gain information from topographic data across different environments.	*Explore/Identify* – point and zoom to areas of interest to determine the shapes of features.	Comparative study of immersion versus non-immersion
Visual comparison of networks in VR (Joos et al., 2022)	*Discover* – explore how weighted networks can be visually compared in an immersive VR environment and investigate how visual representations can benefit from the extended 3D design space.	*Discover* – compare and evaluate the different node-link diagram encodings. *Lookup/Locate /Explore* – find the region containing the edges with the highest accumulated weight differences between both networks. *Compare* – comparing the connectivity between two nodes by evaluating the weight difference of the edges connecting two given nodes.	Evaluating properties of IA

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Table 6. Continued

References	Goals (Application)	Tasks (Users)	Evaluation Types
IATK (Immersive Analytics Toolkit) (Cordeil & Dwyer, 2019)	*Produce* – offers a toolkit that allows interactive authoring and exploration of data visualization in immersive environments.	*Produce* – manipulating the grammar of graphics using high-level interfaces. *Discover* – to seek outliers, trends, and more general structural information in the data. *Explore/Summarize* – explore the data: get more visual detail from the data and leverage bi-manual input to quickly select data points of interest in visualization.	Examples or demonstration
Visualization of real-time heterogeneous smart city data using VR (Broucke & Deligiannis, 2019)	*Present* – present visualization of real-time heterogeneous smart city data of the city of Brussels using VR technology.	*Discover/Compare* – study user experience while exploring smart city data using the proposed VR platform and a web application. *Lookup/Locate/Explore/Identify* – finding and indicating the number of bicycles (target known) left at a random rental station, finding a cluster of social entities, finding a moving public transport vehicle, and describing the vehicle's previous and next stop.	Comparative study of immersion versus non-immersion
Hybrid analytics system for collaborative exploratory data analysis (Cavallo et al., 2019)	*Present* – introduced a hybrid analytics Dataspace application for collaborative exploratory data analysis.	*Discover/Compare* – evaluate the contributions and limitations of immersive technologies in EDA at various levels of the virtuality continuum. *Enjoy/Browse/Explore* – participants can freely analyze a toy dataset focused on indices of wellness for 34 OECD countries. *Lookup/Locate/Identify* – identify the person with the highest participation rate among the cluster of subjects who are most active on weekdays. *Compare* – compare a person's stress and wellness scores with those of the other members of the cluster. *Share* – participants were placed in groups of three so they could collaborate on a team solution.	Comparative study of immersion versus non-immersion
Hybrid asymmetric collaborative immersive analytics system (Reski, Alissandrakis, & Kerren, 2020)	*Present* – present a hybrid IA system to support asymmetrical collaboration between a pair of users during synchronous data exploration.	*Present/Share* – guided/teaching scenario, where one of the users in each session would be a language teacher (expert) along with a language student (novice). *Discover/Compare* – evaluate user performance for collaboration in an immersive environment and non-immersive environment. *Enjoy* – undirected search with no hypotheses given. *Lookup/Locate/Browse/Explore* – an open exploration of the dataset by the participants using their own strategy and pace. *Compare* – comparing regional language distribution of tweets.	Comparative study of immersion versus non-immersion
Exploration of time-oriented data in immersive VR (Reski, Alissandrakis, Tyrkkö, et al., 2020)	*Present* – presented an approach to interact with time-oriented data in VR within the context of IA.	*Produce* – participants were asked to use the annotation functionality and capture some observations. *Discover/Compare* – evaluate if the participants would be able to correctly determine and analyze certain properties of the data. *Enjoy/Lookup/Locate/Browse/Explore* – participants were encouraged to freely explore the data using the functionalities provided through the developed VR application, using their own strategy and pace with no time constraints. *Identify/Compare* – identify min and max values and compare values between different data.	Evaluating properties of IA
CodeCity (Moreno-Lumbreras et al., 2021)	*Present* – leverages the "city metaphor" to represent software systems as cities through an interactive 3D software visualization.	*Discover/Compare* – investigate the affordance of VR in CODECITY-like visualizations as compared to the traditional onscreen representation. *Explore* – explore the city to locate all the test codes. *Lookup/Locate/Identify* – find the three source code files (target known) with the highest amount of functions/line of codes/etc.	Comparative study of immersion versus non-immersion

interaction with 3D graph exploration through VR technology. Arguably, the authors think that the use of visualization to discover information should also include generating or verifying the general hypothesis of an application, such as investigating the effectiveness of different systems (Andersen et al., 2019) and finding out how to visually compare weighted networks in an immersive environment (Joos et al., 2022). Other than that, the authors support that an application introducing a novel interactive means of data visualization (Sun et al., 2020; Walsh et al., 2018) should be included in the *discover* task as there is a need to discover or verify the affordances of using VR in data visualization within the application.

In summary, this subsection defines the goal of the IA application using the high-level tasks in the multi-level typology. Most of the applications aim to present a new approach or communicate information through IA. Additionally, some of the applications leverage IA to discover and verify both scientific and general hypotheses or generate new artifacts. Therefore, the high-level tasks are sufficient to address the reason IA is used in these applications.

Answering: Why Is the Task Performed?

This section aims at answering the question of *Why does the user perform the task?* in the context of the IA application. Unlike the previous question, this involved all tasks in the multi-level typology, which covered the scope from high-level to mid-level to low-level. The tasks were mapped based on the application's evaluation method because further elaboration and description of tasks were mostly found in this section. However, not all tasks were clearly mentioned because the tasks' keywords were unable to be identified during data extraction. Therefore, not all tasks were stated in the mapping result. Other than the studies by Ma et al. (2021) and Chen et al. (2020), all papers were able to be synthesized to answer *why* the task is performed.

At the high level, the *discover* task was used to describe the need for the application to validate and evaluate its effectiveness through examples or demonstration (Huang et al., 2019; Kloiber et al., 2020; Marai et al., 2017; Neto et al., 2015) and evaluation of IA properties (Alfalah et al., 2014; Joos et al., 2022; Pachas-Banos et al., 2019; Reski, Alissandrakis, & Kerren, 2020; Sun et al., 2020). In addition, some of the studies (Broucke & Deligiannis, 2019; Cavallo et al., 2019; Moreno-Lumbreras et al., 2021; Reski, Alissandrakis, Tyrkkö, et al., 2020) combined *discover* and *compare* tasks from the low level as the evaluation method of these applications involved a comparative study between immersion and non-immersion system. The *produce* tasks were mapped to applications that involved the generation of new artifacts. These artifacts included annotations (Kloiber et al., 2020; Reski, Alissandrakis, & Kerren, 2020), clusters of selection (Capece et al., 2018), transformed or manipulated data (Cecotti et al., 2020; Cordeil & Dwyer, 2019), and the creation and combination of groups within the application (Krause-Glau & Hasselbring, 2022; Wolfartsberger et al., 2017).

Furthermore, several applications were mapped to *enjoy* tasks, which referred to users' casual encounters with a visualization. There is a close relationship between casual encounters of visualization and free exploration (Cavallo et al., 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020). Thus, the authors think that *enjoy* could be mapped alongside the *explore* tasks from the mid-level. Capece et al. (2018) mentioned that users can freely explore the 3D visualization in their proposed application. Marai et al. (2017) described that users can freely move through their CAVE2 environment to interact with any point of interest. Apart from that, the *enjoy* task could also be referred to as the interaction with visualization that happened without the need to verify or generate a hypothesis (Reski, Alissandrakis, & Kerren, 2020; Reski, Alissandrakis, Tyrkkö, et al., 2020).

The *searching* tasks at the mid-level were classified according to whether the target and location were known or unknown. The authors argue that it is still an open question as to how these tasks should be mapped because it depends on users' knowledge of the element of interest. For example, the user study by Broucke and Deligiannis (2019) involved the task of finding and indicating the number of bicycles left in a rental station in Brussels. In this task, the target was known (the bicycle); however, it was uncertain to determine if users have the knowledge of the location of the bicycle.

Therefore, both *lookup* and *locate* were mapped to this application even though it was not explicitly stated in the paper. In addition, Cavallo et al. (2019) conducted an evaluation study that required the user to identify the person with the highest participation among subject clusters as one of the tasks. Similarly, the target (person with the highest participation) was known. Whether the users know the target location or not is highly dependent on the users themselves. Arguably, without a specific or explicit mention of the *searching* task keywords in the description, the mid-level tasks could be mapped based on justified assumptions.

In some of the applications, the terms used to describe the search tasks were ambiguous, such as "go through all the nodes" (Capece et al., 2018), "walk and look around the environment" (Sun et al., 2020) and "navigate within the graph nodes" (Neto et al., 2015). In this case, these applications were generally mapped to *explore* tasks because there was no mention of the target or the target's location.

At the low-level, the task of *identifying* can be performed with a single target (Andersen et al., 2019; Capece et al., 2018; Kloiber et al., 2020; Oliveira et al., 2021; Pick et al., 2016), *comparison* for multiple targets (Alfalah et al., 2014; Cavallo et al., 2019; Huang et al., 2019; Joos et al., 2022; Reski, Alissandrakis, & Kerren, 2020; Reski, Alissandrakis, Tyrkkö, et al., 2020), and *summarize* for the entire dataset (Cecotti et al., 2020; Neto et al., 2015; Oliveira et al., 2021; Walsh et al., 2018). In addition, the *share* tasks were mapped to collaborative applications like the hybrid analytics system by Cavallo et al. (2019) and the hybrid asymmetric IA system by Reski, Tyrkkö, et al. (2020). Additionally, the Endurance case study (Marai et al., 2017) allowed users to *share* data through an interactive session.

To conclude, all levels of tasks in the multi-level typology are required to answer why users performed the task within an IA application. The high-level tasks help to identify the tasks' general objective, the mid-level for searching tasks, and the low-level to specify the query. Due to lack of clarity of the terms, some of the tasks were mapped without being mentioned explicitly. This has been previously justified by the authors.

RQ2: Systematic Mapping of IA Integrated Application Scenario

To answer *when* to integrate IA in the analytical application, this article explores the application domains and guiding scenarios as reported in previous works. For the first topic, the authors delved into the application domains where the IA is implemented. Meanwhile, the second topic associated the domains with potential scenarios. The novelty of this study also includes the addition and adaptation of new scenarios to complement the work by Kraus et al. (2021) based on the evidence found in the previous research.

Application Domains

Table 7 shows the compilation of the application domain as reported by previous works. GIS had the most research studies, which consisted of 11 articles. Next, the healthcare domain had five articles. Both computer science and engineering had three articles each. Meanwhile, architecture and astronomy recorded only one article each. There were four articles targeted for general purpose or did not state its specific domain. Note that there are several articles that provide multiple application domains that implemented the IA (Cavallo et al., 2019; Marai et al., 2017).

In GIS, four studies focused on environmental science, such as meteorology (Andersen et al., 2019), forestry (Huang et al., 2019), geology (Ma et al., 2021), and biochemical (Marai et al., 2017). Smart city and urban planning had three studies; social media analytics had two studies. Social media analytics was classified as GIS because these studies involved the use of geolocation dataset to explore the language variability on social media in the Nordic region (Reski, Alissandrakis, & Kerren, 2020; Reski, Alissandrakis, Tyrkkö, et al., 2020). Two IA studies in GIS do not have specific subdomains. These can be applied to other geographical and location datasets, such as the inspection of archeological sites (Bennett et al., 2015) and space-time cube visualization (Walsh et al., 2018). The results show that numerous GIS applications utilized the benefit of IA to analyze and understand geographical datasets. The main reason is the suitability of IA to visualize 3D geolocation and spatial

Table 7. Application domains and references

Application Domain	Sub-Domain	Number of References	References
Architecture	Design Review	1	(Pick et al., 2016)
Astronomy	-	1	(Marai et al., 2017)
Computer Science	Information Management	1	(Neto et al., 2015)
	Software Engineering	2	(Krause-Glau & Hasselbring, 2022; Moreno-Lumbreras et al., 2021)
Engineering	Automotive	1	(Oliveira et al., 2021)
	Industrial Engineering	1	(Wolfartsberger et al., 2017)
	Industrial Science	1	(Kloiber et al., 2020)
GIS	Environmental Science	4	(Andersen et al., 2019; Huang et al., 2019; Marai et al., 2017; Ma et al., 2021)
	Smart City and Urban Planning	3	(Broucke & Deligiannis, 2019; Chen et al., 2020; Sun et al., 2020)
	Social Media Analytics	2	(Reski, Alissandrakis, & Kerren, 2020; Reski, Alissandrakis, Tyrkkö, et al., 2020)
	Others	2	(Bennett et al., 2015; Walsh et al., 2018)
Healthcare	Health Informatics	1	(Cavallo et al., 2019)
	Medical Imaging	3	(Cecotti et al., 2020; Joos et al., 2022; Marai et al., 2017)
	Musculoskeletal	1	(Alfalah et al., 2014)
Others	-	4	(Capece et al., 2018; Cavallo et al., 2019; Cordeil & Dwyer, 2019; Pachas-Banos et al., 2019)

data where it provides the sense of place and rich experiences for the users. Efficient user interactions can also improve the spatial understanding of users when exploring visualization, such as the ability to overview and zoom in to a specific location instantly.

IA application also attracted the attention of the healthcare domain. There were three studies that used IA to analyze the medical imaging datasets, particularly magnetic resonance imaging (MRI). There was one study on skeletal gait analysis (Alfalah et al., 2014) and one study on disease informatics analysis (Cavallo et al., 2019). Based on previous works, the application of IA in healthcare is diverse. It ranged from the 3D reconstruction of anatomy to information systems. The ability to analyze the 3D inners anatomy can enhance the understanding of medical practitioners without a heavy mental workload to transform a set of 2D imaging into 3D impression mentally (Mohamed & Siang, 2019).

On the other hand, medical data and patient records can be utilized in IA for practitioners to explore the relationship between data and provide a platform for collaboration.

For the computer science domain, information management recorded only one research that analyzed the relational database (Neto et al., 2015). In contrast, there were two IA applications on software engineering to improve program comprehension in software review (Krause-Glau & Hasselbring, 2022; Moreno-Lumbreras et al., 2021). In contrast to the previous domains, IA applications in computer science make use of appropriate visual encodings and metaphor embellishment to visualize the relationship between abstract datasets (for example, relational database and software system architecture). Furthermore, effective user interaction design can increase the usability of IA when exploring these abstract datasets.

In addition, the engineering domain has one record for each of the following sub-domains: automotive (Oliveira et al., 2021); industrial engineering (Wolfartsberger et al., 2017); and industrial science (Kloiber et al., 2020). IA was utilized in the one construction's design review of architecture domain (Pick et al., 2016). These projects showed that the IA can assist in the design and analysis process by simulating the working prototype of engines or buildings virtually and remotely. Besides, IA can aid in the exploratory visual analytics of real-time sensor datasets by providing various means of user interaction to manipulate the data and views.

Regarding the environment that is difficult to reach by humans, such as outer space, IA can visualize both the environment and its data. This is essential for scientists to analyze, discuss, and present their findings to improve their understanding. There is one study concentrated on the simulation of dark matter formation (Marai et al., 2017). Lastly, there were four articles in the other domains as they did not specify the dataset attributes or domain of interest and can be reproduced for other domains (Capece et al., 2018; Cavallo et al., 2019; Cordeil & Dwyer, 2019; Pachas-Banos et al., 2019).

In summary, IA has been applied to various domains where its intrinsic 3D visualization capability combined with suitable usage of visual encodings and intuitive user interaction can provide a powerful tool that brings new perspectives for humans to analyze and relate the dataset. In the next subsection, the authors elaborate on the discussion of application domains with IA guiding scenarios and the evidence found in previous studies. This is useful to pilot the future researchers to design an effective IA application.

IA Guiding Scenarios

Kraus et al. (2021) associated the compiled application domains with guiding scenarios that maximize the benefits of IA in data analysis. This work also adapted and modified these guiding scenarios, as shown in Figure 4. In addition, Figure 5 shows the bubble chart of relationship between application domains and IA guiding scenarios. It encodes the intersecting bubble nodes with the number of publications reporting the related scenarios.

Figure 4. Comparison of original four guiding scenarios and the adapted version

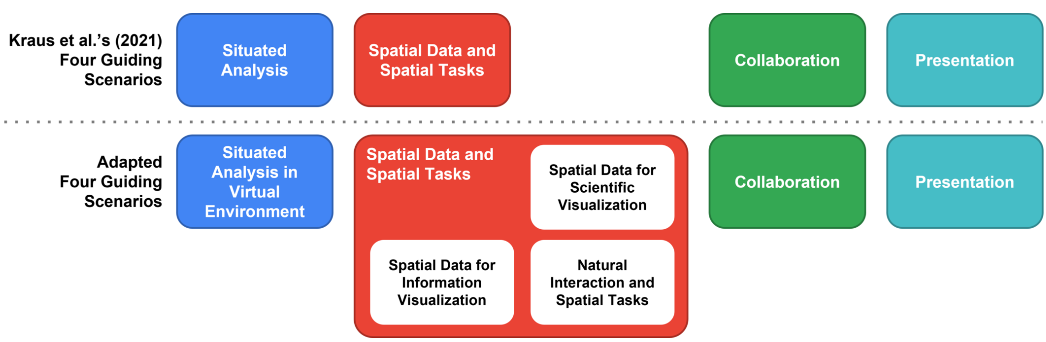
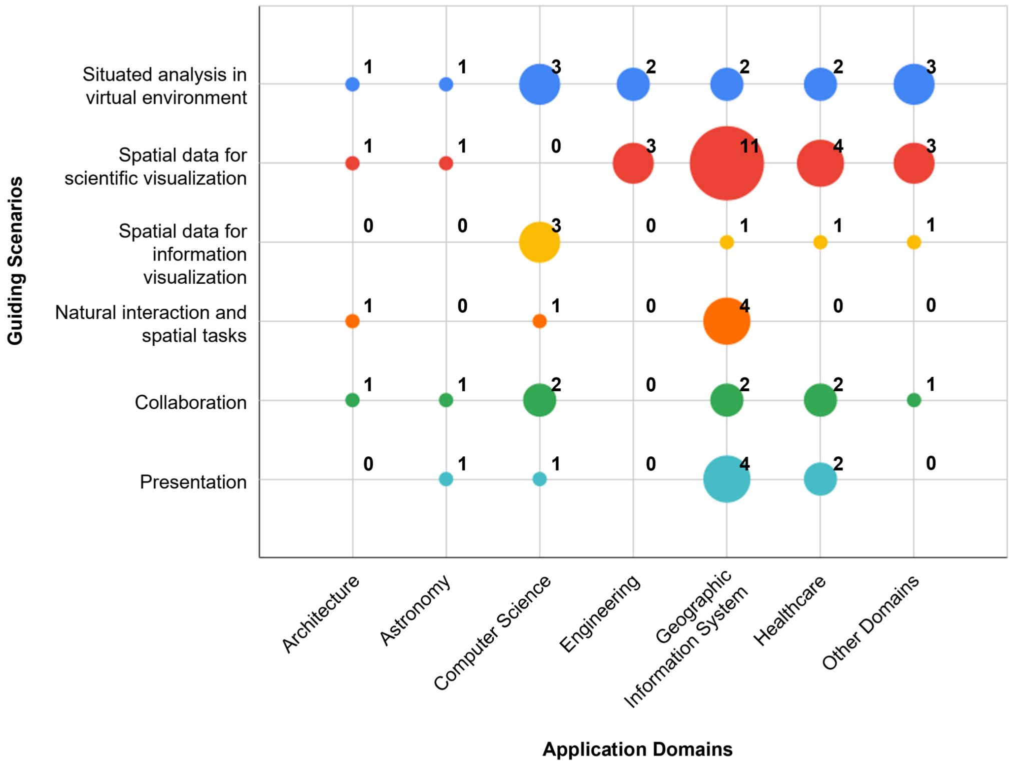


Figure 5. Application domains and guiding scenarios



In most cases, situated analysis refers to the use of AR to present additional information superimposed on the real environmental object through smartphone's screen display or AR glasses (Kraus et al., 2021). However, this analysis type can be realized in the immersive virtual environment, where users can interact with the virtual objects by viewing the embedded data for analysis. The IA applications provide various means of detail-of-demand tasks. For example, it can annotate data in the 3D space for sharing knowledge with other users (Pick et al., 2016) and expanding the information saved in tooltips and data labels located near the data objects of interest (Krause-Glau & Hasselbring, 2022; Moreno-Lumbreras et al., 2021). The use of virtual environments also allows users to dive into the "real" but simulated environment and analyze the surrounding data, particularly for the real environment that is difficult to reach, such as the bottom of the lake (Marai et al., 2017) or a large geographical area (Broucke & Deligiannis, 2019).

The second guiding scenario is spatial data and spatial tasks. Due to the diverse data types and interactions found in the collected evidence, the authors divided this scenario into three sub-scenarios: (1) spatial data for scientific visualization (SciVis); (2) multidimensional data for information visualization (InfoVis); and (3) natural interaction and spatial tasks. Based on previous works, the main motivation to use IA is to show spatial data for SciVis as it has the most focused topic in various application domains, especially GIS, healthcare, and engineering. The data used in SciVis has the characteristics of 3D spatial elements suitable to view in 3D space and improve spatial understanding, such as the surface of the earth (Bennett et al., 2015; Ma et al., 2021), inner structure of a body (Cavallo et al., 2019; Cecotti et al., 2020), or architecture of a building (Pick et al., 2016). The visualization of spatial data provides a higher sense of presence, data immersion, and overview (Bennett et al., 2015;

Broucke & Deligiannis, 2019) when compared to non-immersive methods, such as those based on a monitor screen. Although IA has high user preference and suitability for viewing spatial data, there was one study that found out that the number of complete observations in IA was less than the 2D and 3D desktop-based visualization methods (Bennett et al., 2015). The results were due to the knowledge bias the specialists experienced in using the 2D tools and lack of user interactions observed in the IA method. Hence, future researchers should consider the participants' background and provide proper demonstration before the testing session or utilizing tooltips in the IA application.

On the other hand, InfoVis is less utilized for IA, as shown in Figure 4. The rationale is due to the more efficient visualization of abstract dataset using traditional 2D methods, such as bar charts, line charts, and treemaps. However, a well-designed visualization and user consideration can increase the usability of IA applications. Previous works showed that IA was effective in displaying relationships between datasets and performing comparative analyses. For example, Joos et al. (2022) compared the user performance between a 2D matrix view and 3D network. They concluded that the participants using the 3D network in IA application had higher accuracy than with the 2D method. The ability to rotate the 3D visualization can also help solve the high-density data relationship (or "hairballs") issue. Besides, Cordeil et al. (2019) created a user-friendly open source IATK to help users create various 2D and 3D charts in immersive environments without programming knowledge based on multidimensional tabular dataset. They also introduced the graphics grammar to facilitate the design and creation of InfoVis, including the view-frames, visual encodings, linking, and summarization.

After data visualization, the IA application should allow users to perform data analysis by interacting with data objects. IA can capitalize the natural movement and motion to provide intuitive spatial tasks when users interact with the immersive visualization. Previous research utilized the controllers (Moreno-Lumbreras et al., 2021; Pick et al., 2016), gesture-based interfaces like Leap Motion (Andersen et al., 2019; Reski, Alissandrakis, & Kerren, 2020; Reski, Alissandrakis, Tyrkkö, et al., 2020), and other specialized devices (Walsh et al., 2018) to select, move, and transform the data object of interest in 3D space. Compared to traditional mouse and keyboard input devices, hand-held controllers and Leap Motion gesture input in immersive medium reported that most users are able to perform the evaluated tasks, have good usability scores, and realized higher satisfaction among the participants (Andersen et al., 2019; Reski, Alissandrakis, & Kerren, 2020). One study also found out that the controller had more accurate results than gesture-based methods although gesture interaction was enjoyable to use (Andersen et al., 2019). Therefore, there is a need to improve gesture-based methods to facilitate a more detailed and accurate performance.

In the third guiding scenario, IA application shows its advantages in collaboration whether in a co-located (Cavallo et al., 2019; Marai et al., 2017; Neto et al., 2015; Reski, Alissandrakis, & Kerren, 2020) or remote (Krause-Glau & Hasselbring, 2022) environment. They were implemented in diverse application domains, including architecture, astronomy, computer science, GIS, and healthcare. In the co-located collaborative environment, most of the past research utilized the VR HMD (Cavallo et al., 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020), the CAVE (Marai et al., 2017; Neto et al., 2015; Pick et al., 2016), and multiple display system (Cavallo et al., 2019). This allowed users to explore the data together before they transformed and shared the findings with their peers in the same environment. Some solutions cater to a hybrid environment in which users can perform data transformation and analysis by using their own devices in their individual workspace without affecting the main projection screen (Neto et al., 2015). They can also share their findings with their colleagues on demand (Marai et al., 2017), promoting agency and teamwork skills.

Moreover, with the integration of emergent cloud technology, IA's influence in remote collaboration cannot be diminished. The Internet can connect all users in a virtual space without being physically together in the real world. Users from different continents can collaborate in a situated visualization for analyzing data and joining the discourse. The preceding research explored the capability of remote collaborative IA in software reviews where the users can move and engage in discussion with their peers in the same VR world (Krause-Glau & Hasselbring, 2022). The IA application should also include synchronization features, providing consistent views to all users in the same session (for example, highlighting the linking data in user views).

Aside from the exploratory scenarios like situated analysis, spatial tasks, and collaboration, explanatory application is important to transfer knowledge to audiences and promote efficient scientific communication. The audience types can range from experts to stakeholders to non-experts to the public. Hence, IA can bring added values to the presentation scenario. It is not limited to presenting the virtual environment. Instead, it can facilitate the guided navigation. Like the collaboration scenario, presentation can employ the CAVE system (Chen et al., 2020; Ma et al., 2021; Neto et al., 2015), projection system (Alfalah et al., 2014), and hybrid systems that involved a screen and VR HMD (Marai et al., 2017; Reski, Alissandrakis, Tyrkkö, et al., 2020) to accommodate the masses. Users can use the IA application and equipment to demonstrate the design to stakeholders or fellow researchers, such as in energy grid planning (Chen et al., 2020), gait representation and movement (Ma et al., 2021), and relational database network graphs (Neto et al., 2015).

Besides that, guided navigation during an IA presentation can improve the understandability of audiences, especially non-experts. Previous studies utilized IA technologies, such as CAVE, to perform the evolution and formation of a massive cosmological dark matter visualization in a planetarium (Marai et al., 2017). The audiences remarked on the suitability of IA in guided presentations where they never felt lost and can learn interesting knowledge at a focus point of interest.

RQ3: IA Value Assessment Methods

This section investigates and compiles the research methodologies and evaluation methods to assess the value of IA application. A proper assessment and hypothesis testing can help to respond to *why* and *when* it is useful to integrate IA in everyday analytical tasks, demonstrate its advantages for problem solving, and explore the drawbacks of IA for future challenges. It can also help to provide remedies for improving the user experience and performance when using IA applications, such as visual encodings, interactions, and functional requirements.

To answer this research question, the authors first compiled the evaluation types, research methods, and references (see Table 8). The systematic mapping of evaluation types is based on Kraus et al.'s (2021) IA value assessment types. The research method includes method types, research approaches, and instruments reported in preceding studies.

Figure 6 shows the Sankey diagram that depicts the interconnectedness of three domains: (1) evaluation types; (2) research methods; and (3) instruments used. This visualization helps to map these domains in a many-to-many relationship to answer the researchers' inquiries and assist in choosing a suitable research method and instruments for evaluation. Note that some research methods performed more than one research method or instrument in the same research; hence, the increased aggregate number of instruments is compared to the aggregate number of research methods or evaluation types. The aggregate number of research methods also has more than the aggregate number of evaluation types.

Based on the systematic mapping, the examples or demonstration evaluation type had a total of 12 studies, evaluating properties of IA had eight studies, and comparative study of immersion and non-immersion had six studies. Andersen et al. (2019) consisted of two types of evaluation (the second and third evaluation types). There were five research methods identified from previous works, in which the use case method was the most used method with 13 studies reported. It was followed by usability and user experience (UX) studies and user performance analysis, which recorded 10 and 9 studies, respectively. Meanwhile, case study method and mental workload study had four and three studies, respectively.

Furthermore, the instruments for qualitative analysis consisted of nine demonstration or example studies, seven studies used observation and recordings, six studies implemented think aloud protocol, and three semi-structured interviews conducted previously. On the other hand, there were eight user performance experiments, three research employed system usability scale (SUS) questionnaires, and

Table 8. Evaluation types and methods with numbers inside parentheses representing number of studies reported

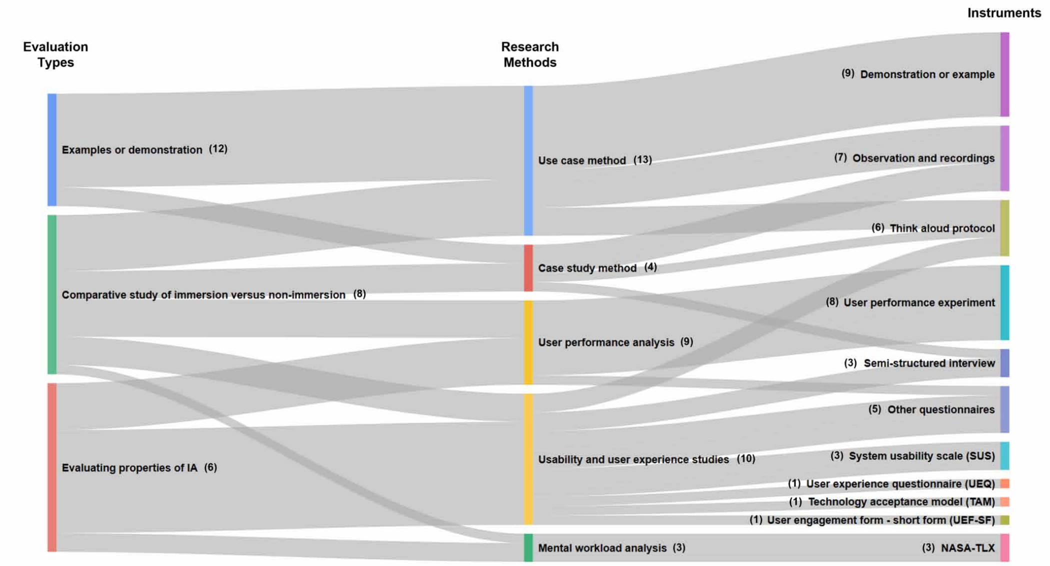
Evaluation Types	Research Methods	References
Examples or demonstration (12)	**Use case or descriptive method (10)** **Research approach:** Qualitative analysis **Instruments:** Demonstration (9), observation and recording (1)	(Capece et al., 2018; Cecotti et al., 2020; Chen et al., 2020; Cordeil & Dwyer, 2019; Huang et al., 2019; Krause-Glau & Hasselbring, 2022; Ma et al., 2021; Neto et al., 2015; Oliveira et al., 2021; Walsh et al., 2018)
	Case study method (2) **Research approach:** Qualitative analysis **Instruments:** Observation and recording (2)	(Kloiber et al., 2020; Neto et al., 2015)
Evaluating properties of IA (8)	**User performance analysis (5)** **Research approach:** Quantitative analysis **Instruments:** User performance experiments (task accuracy, completeness, duration, etc.) (5) **Metrics:** Task accuracy, comprehension and understanding, completion time.	(Andersen et al., 2019; Joos et al., 2022; Pachas-Banos et al., 2019; Pick et al., 2016; Sun et al., 2020)
	Usability and user experience studies (7) **Research approach:** Quantitative analysis & qualitative analysis **Instruments:** System usability scale (SUS) (2), user experience questionnaire (UEQ) (1), technology acceptance model (TAM) (1), questionnaires (2), user engagement form - short form (UEF-SF) (1), think aloud protocol (2), semi-structured interview (2) **Metrics:** Perceived usefulness, perceived ease of use.	(Alfalah et al., 2014; Andersen et al., 2019; Joos et al., 2022; Pachas-Banos et al., 2019; Pick et al., 2016; Reski, Alissandrakis, & Kerren, 2020; Wolfartsberger et al., 2017)
	Mental workload analysis (2) **Instrument:** NASA-TLX (2). **Research approach:** Quantitative analysis	(Joos et al., 2022; Pick et al., 2016)
Comparative study of immersion versus non-immersion (6)	**User performance analysis (4)** **Research approach:** Quantitative analysis **Instruments:** Questionnaires (1), user performance experiment (3) **Metric:** Accuracy of selection, completion time, completeness (count of observation)	(Andersen et al., 2019; Bennett et al., 2015; Cavallo et al., 2019; Moreno-Lumbreras et al., 2021)
	Usability and user experience studies (3) **Research approach:** Quantitative analysis & Qualitative analysis **Instruments:** Questionnaires (2), System usability scale (SUS) (1) **Metrics:** Usability, suitability, perceived levels of data intuitivity, distinction, immersion, overview, and intuitive interaction	(Andersen et al., 2019; Broucke & Deligiannis, 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020)
	Mental workload analysis (1) **Research approach:** Quantitative analysis **Instrument:** NASA-TLX (1)	(Broucke & Deligiannis, 2019)
	Use case method (3) **Research approach:** Qualitative analysis **Instruments:** Think aloud protocol (3), observation and recording (3)	(Bennett et al., 2015; Cavallo et al., 2019; Moreno-Lumbreras et al., 2021)
	Case study method (2) **Research approach:** Qualitative analysis **Instruments:** Think aloud protocol (1), semi-structured interview (1), observation and recording (1)	(Cavallo et al., 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020)

three studies of NASA Task Load Index (NASA-TLX). The remaining questionnaires had one study each. Meanwhile, there were five studies that implemented other questionnaires.

Examples or Demonstrations

This subsection describes the features of the IA system or application. The two types of research methods are use case or descriptive method and case study method. The use case or descriptive method presents the application usages and features that can be deployed in the real environment. Researchers demonstrated the analytical tasks provided by IA applications for addressing possible user scenarios and problems (Cecotti et al., 2020; Cordeil & Dwyer, 2019; Neto et al., 2015; Walsh et al., 2018). In contrast, the case study method observes the performance of domain experts during a real-life working analytic session (Kloiber et al., 2020; Marai et al., 2017).

Figure 6. Evaluation types, method, and instruments used



Generally, the descriptive method lacks evaluation elements because researchers explained application features only. For user case and case study methods, researchers need to provide the information regarding the experiment setup, including the participants, tasks to conduct and observe, data collection method and instrument, and standard operating procedure.

Evaluating Properties of IA

The second evaluation type is to assess the properties of IA application, such as the user performance, usability, suitability, and user acceptance. Researchers can also conduct the experiment to compare the efficiency between different interactions (Andersen et al., 2019), visual designs (Joos et al., 2022), and workflows (Pick et al., 2016) in IA application. Most previous works implemented quantitative analysis in terms of user performance analysis, usability and UX studies, and mental workload to measure the properties of IA application. In the user performance analysis, researchers conducted experiments where participants needed to complete several tasks to measure the efficiency and effectiveness of the IA application. Most of the metrics used are task accuracy (Joos et al., 2022; Pick et al., 2016; Reski, Alissandrakis, Tyrkkö, et al., 2020; Sun et al., 2020), completion time (Andersen et al., 2019; Joos et al., 2022; Pick et al., 2016), and comprehension and understanding (Pachas-Banos et al., 2019).

Furthermore, the usability and UX studies can determine the system's usability and user behavior or perception to use the IA system. The researchers can adopt both quantitative and qualitative analyses. The instrument for quantitative analysis includes system usability scale (SUS) (Pick et al., 2016; Reski, Alissandrakis, Tyrkkö, et al., 2020), user experience questionnaire (UEQ) (Pick et al., 2016), technology acceptance model (TAM) (Alfalah et al., 2014), and user engagement form-short form (UEF-SF) (Reski, Alissandrakis, & Kerren, 2020). As for qualitative analysis, researchers can utilize think aloud protocol to allow participants to speak their mind during the interaction session with the IA application (Reski, Alissandrakis, & Kerren, 2020; Wolfartsberger et al., 2017) or conduct a semi-structured interview after the session (Pachas-Banos et al., 2019; Reski, Alissandrakis, & Kerren, 2020).

In addition, mental workload evaluation ensures that the IA application does not cause user frustration and heavy mental load when performing analysis tasks. Most previous works employed the NASA-TLX to measure the mental workload of IA application for choosing the 3D data visualization design with lower mental load (Joos et al., 2022) and studying which guided navigation had less stress result (Pick et al., 2016). In this regard, future studies should consider the elements of user performance, usability, and mental stress to design and evaluate an effective and efficient IA application.

Comparative Study of Immersion vs. Non-Immersion

The comparative study involves the assessment between immersive and non-immersive analysis task scenarios to measure the immersive values of IA. It answers why it affects the efficiency and effectiveness during analysis. According to Kraus et al. (2021), it can contribute to the understanding of which immersive situation is best or worst for the data analytics application. Most of the studies compared the data visualization application on PC and VR HMD or CAVE system (Andersen et al., 2019; Bennett et al., 2015; Broucke & Deligiannis, 2019; Moreno-Lumbreras et al., 2021; Reski, Alissandrakis, & Kerren, 2020). Besides, there were several studies that compare hybrid immersive collaborative scenarios, including screen displays, VR, and AR technologies (Cavallo et al., 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020).

This evaluation type implements the same research methods as the second evaluation type to measure the properties of IA, including performance analysis, usability and UX studies, and mental workload analysis. However, the second type measures the strengths of IA application in terms of performance and usability, while this comparative study answers and justifies the needs for using immersive elements in the data visualization tasks. The research methodologies can be classified as a within-subjects experiment (Andersen et al., 2019; Broucke & Deligiannis, 2019; Cavallo et al., 2019; Reski, Alissandrakis, Tyrkkö, et al., 2020) and between-subjects experiment (Bennett et al., 2015; Moreno-Lumbreras et al., 2021). A within-subjects experiment requires that all participants conduct the same tasks in different scenarios. Meanwhile, a between-subjects experiment breaks the participants into two or more groups to experience different conditions or to segregate participants with different backgrounds (for example, experts and novices).

Besides, researchers can implement use case and case study methods to study users' behavior when using IA applications. These research methods allow the researchers to observe and discover how the users perform the data analysis action and use the interaction (Bennett et al., 2015), what questions the participants asked (Reski, Alissandrakis, Tyrkkö, et al., 2020), and how the participants work together to solve a problem (Cavallo et al., 2019). Aside from conducting a semi-structured interview at the end of the evaluation session to get users' feedbacks (Moreno-Lumbreras et al., 2021), researchers can also write down participants' thoughts, record the videos and audios during the session, and analyze participants' notes (Bennett et al., 2015; Cavallo et al., 2019) for further analysis.

THREAT OF VALIDITY

The limitations and future studies identified in this study were discussed as follows:

- **Data Ambiguity:** The ambiguity of terms used in the selected works was considered a limitation of this study. The lack of clarity in some of the words being used, such as navigate and interact, made it difficult to map the tasks accordingly. Additionally, the authors planned to include an extension of tasks in the low-level (query) based on Mariott et al. (2018). These are *guide*, *build*, and *use*. However, due to a lack of matching terms, there were few tasks extracted. They were, therefore, excluded from the result.
- **Lack of Databases:** This work only searched in the IEEE Xplore and ACM Digital Library. However, these databases host numerous high-impact journals and conference proceedings of computer graphics, data visualization, and extended reality technologies. Examples include IEEE Transactions on Visualization and Computer Graphics (IEEE TVCG), ACM Computing Surveys, ACM Symposium on Virtual Reality Software and Technology (VRST), and IEEE Symposium

on Visual Analytics Science and Technology (VAST). In the future, authors should consider Eurographics, Elsevier, and Springer because they contain high-quality journals and conference proceedings like Computer Graphics Forum and Computers & Graphics.

- **Publication Bias:** This study did not consider publication bias where there is a possibility that the past researchers did not publish the full results in the articles or only published the data with positive results (Kitchenham et al., 2007; Liberati et al., 2009). To mitigate the influences of this effect, the authors performed several maneuvers by scanning the articles fully and designing a data extraction strategy. These practices reflected the collection of results like the tasks completeness issue in IA, issues found in assessments, and conducting experiments to choose the preferred interactions or visual encodings (Andersen et al., 2019; Bennett et al., 2015; Joos et al., 2022).
- **Threat of Informativeness:** There were several studies that only presented examples or demonstrations of IA systems. Therefore, special efforts were conducted to obtain high quality studies by using the quality assessment method as reported in the Analytical Stage subsection. Articles with lower quality scores were excluded for the data analysis and synthesis stage.

CONCLUSION AND FUTURE WORK

In this article, an overview of IA applications was presented based on the typology of visualization tasks and application scenarios. This work also explored the IA value assessment methodologies to provide recommendations and guidelines that facilitate IA application creation and evaluation. The authors reviewed related works to understand the research background and analyzed the relevant articles collected from systematic searching. Based on the result, 25 original works were synthesized to answer three research questions. The first research question answers the *why* part of the multi-level typology framework within three levels of specificity: high-level, mid-level, and low-level tasks. This section addressed the goal of an IA application using high-level tasks and the reason users performed IA-related tasks using all three levels of task specificity. A comprehensive mapping was compiled. Due to the ambiguity of terms, the result was not able to be expanded to cover broader low-level terms.

Then, the authors classified the application domains and guiding scenarios to answer *when* to integrate the IA application. In this part, the authors discussed the application domains in which the IA is implemented. They associated them with potential scenarios. Moreover, the authors adapted existing literature and produced a novel scenario-based guide to help maximize the benefits of IA in data analysis. In the future, AR technology should be included in the future literature review for advancing the knowledge of IA application development.

Last, this study investigated the research methodologies and evaluation methods that assess the value of IA applications to understand *why* and *when* it is useful to integrate the IA. This section is dedicated to answering the last research question by analyzing its advantages for problem-solving and the drawbacks of IA for future challenges. It also can help the researchers choose a suitable research method and instruments for evaluating potential future IA applications.

ACKNOWLEDGMENT

The Ministry of Higher Education (MOHE), Malaysia sponsored this research through the Fundamental Research Grant Scheme (FRGS/1/2020/ICT06/UTM/02/2) with vote number 5F395. An extended thank you to Universiti Teknologi Malaysia (UTM) and School of Computing UTM for the guidance on publishing this work. A. Iglesias would like to acknowledge the financial support from the European Union's Horizon 2020 research and innovation program, Marie Sklodowska-Curie action, RISE program, of the project PDE-GIR with grant agreement reference number 778035, and also from the Agencia Estatal de Investigacion (AEI) of the Spanish Ministry of Science and Innovation, for the grant of the Computer Science National Program with reference number #PID2021-127073OB-I00 of the MCIN/AEI/10.13039/501100011033/FEDER, EU.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

FUNDING AGENCY

This research was supported by the Ministry of Higher Education (MOHE), Malaysia through the Fundamental Research Grant Scheme (FRGS/1/2020/ICT06/UTM/02/2) with vote number 5F395. The financial support for A. Iglesias was obtained from the European Union's Horizon 2020 research and innovation programm, Marie Sklodowska-Curie action, RISE program, of the project PDE-GIR with grant agreement reference number 778035, and the Agencia Estatal de Investigacion (AEI) of the Spanish Ministry of Science and Innovation, for the grant of the Computer Science National Program with reference number #PID2021-127073OB-I00 of the MCIN/AEI/10.13039/501100011033/FEDER, EU.

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