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# Grand Challenges in Immersive Analytics

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## ABSTRACT

Immersive Analytics is a quickly evolving field that unites several areas such as visualisation, immersive environments, and human-computer interaction to support human data analysis with emerging technologies. This research has thrived over the past years with multiple workshops, seminars, and a growing body of publications, spanning several conferences. Given the rapid advancement of interaction technologies and novel application domains, this paper aims toward a broader research agenda to enable widespread adoption. We present 17 key research challenges developed over multiple sessions by a diverse group of 24 international experts, initiated from a virtual scientific workshop at ACM CHI 2020. These challenges aim to coordinate future work by providing a systematic roadmap of current directions and impending hurdles to facilitate productive and effective applications for Immersive Analytics.

## CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**; **Visualization systems and tools**; *Virtual reality*; *Mixed / augmented reality*.

## KEYWORDS

Immersive analytics, grand research challenges, data visualisation, augmented reality, virtual reality

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## 1 INTRODUCTION

An *immersive* system is one whose technology allows us to “step through the glass” [126] of a computer display to engage in a visceral experience of interaction with digitally-created elements. As immersive technologies have rapidly matured to bring commercially successful virtual and augmented reality (VR/AR) devices and mass market applications, researchers have sought to leverage its benefits, such as enhanced sensory perception and embodied interaction [34], to aid human data understanding and sensemaking. This aspiration has brought together researchers from data visualisation, human-computer interaction (HCI), computer graphics, and virtual reality to create a new field known as *Immersive Analytics*.

Since its definition half a decade ago [20], Immersive Analytics has exploded into a rapidly growing body of research on novel interaction techniques, toolkits and applications. There have been numerous scientific community-building and knowledge-dissemination activities including workshops, seminars, a textbook, journal special

issues, and an extensive survey. Recent qualitative and quantitative studies have begun to show concrete evidence of the tangible benefits of immersive systems as well as growing evidence-based guidelines for immersive visualisation design. As the field continues to grow and bridge to related fields, such as interaction design, psychology, machine learning, or computer vision, it becomes important to develop a unified research agenda to facilitate a shift towards enabling productive and effective applications.

In this paper, we describe a set of 17 challenges, grouped into 4 topics: *Spatially Situated Data Visualisation*, *Collaborative Analytics*, *Interacting with Immersive Analytics Systems*, and *User Scenarios & Evaluation*. These 17 new challenges complement previously suggested goals for Immersive Analytics as reviewed in Section 2, but are derived from the most pressing concerns for immersive analytics systems to succeed productively in the wild. This paper takes a community-focused approach, sourcing its set of challenges from a wide range of disciplines and expertise. Our challenges were defined through collective discussion involving 24 experts in the domains of visualisation, virtual and augmented reality, and HCI. Following a structured workshop with 3 sessions and a 3-month collaboration, we converged towards the final 17 challenges (Table 1). Similar to other compilations of grand challenges in HCI, such as recent works on shape changing interfaces [2] and human-computer integration [95], our survey aims to bring the growing community together, to inform common research goals, to help onboard researchers new to Immersive Analytics, and to provide a coherent view to outside stakeholders such as companies and funding agencies.

The remainder of this paper is structured as follows: Section 2 reports the history of Immersive Analytics and the most recent developments from the past 3 years (2018–2020) to provide an up-to-date overview of the state-of-the-art. Section 3 details our workshop methodology. Sections 4–7 each cover one of our 4 challenge topics and Section 8 finishes the paper with discussion and reflection.

## 2 THE EVOLUTION OF IMMERSIVE ANALYTICS

This section surveys various efforts from a number of different fields in HCI, data visualisation and visual analytics as well as VR and computer graphics, to create a firm basis and definition for the emerging field of Immersive Analytics. We review this evolution and then focus on recent results which demonstrate the promise of the field.

### 2.1 Mapping a New Domain

Various recent efforts have aimed to structure the domain of Immersive Analytics, to define challenges and research goals as well as to build a global community of researchers from different fields. Such efforts include:

- **Definitions:** Several authors have proposed definitions about what Immersive Analytics is and what it aims to achieve. In 2015, Chandler et al. [20] explain the goal of Immersive Analytics as to “*explore the applicability and development of emerging user-interface technologies for creating more engaging and immersive experiences and seamless workflows for data analysis applications*”. Later, Marriott et al. [89] add

that Immersive Analytics aims to “*support data understanding and decision making*”. Alternatively, Hackathorn and Margolis [59] emphasise collaboration in their definition “*to enhance collaborative decision support*”. A more recent approach by Skarbez et al. [125] describes Immersive Analytics as “*the science of analytical reasoning facilitated by immersive human-computer interfaces*”, situating it with respect to the knowledge generation loop [106].

- **Survey:** Over the past years, the field has produced an increasing number of publications, extensively summarised in a 2019 survey [51]. Many papers describing and evaluating techniques for visualisation and interaction, evaluating perception or enabling collaboration, have been accompanied and enabled by a series of seminars and workshops.
- **Conference Workshops:** A series of followup workshops were conducted, hosted in major visualisation and HCI venues (ACM ISS 2016 [7], IEEE VIS 2018 [5], CHI 2019 [6] and CHI 2020 [45]). These events focused on topics such as 3D visualisation, perception, interaction, collaboration and evaluation.
- **Scientific Seminars:** The first workshop to involve data visualisation and VR/AR research was organised by Marriott et al. at Shonan in 2015<sup>1</sup>. 2016 then saw a Dagstuhl Seminar [35] involving around 40 researchers and practitioners from data visualisation, VR, and HCI. Another Shonan seminar was held in 2018<sup>2</sup>.
- **Textbook:** The main outcome of the Dagstuhl seminar was the writing of the book *Immersive Analytics* [89]. The book contains chapters on topics such as collaboration, 3D perception, storytelling, and multi-modality. However, the book, being a relatively early foray into the field, primarily discusses opportunities, rather than challenges.
- **Scientific Tutorials and Courses:** An Immersive Analytics Toolkit course was held at IEEE BDVA 2018<sup>3</sup> and IEEE VIS 2018<sup>4</sup>. Two similar courses were held at Siggraph Asia 2019 [42] and ACM ISS 2019 [28].
- **Special issue:** 2019 saw a Special Issue on Immersive Analytics of IEEE Computer Graphics & Applications [43], with articles reflecting on 20 years of evolution of CAVE and immersive analytics systems [87].
- **Recent challenges:** In 2019, Skarbez et al. [125] define 5 challenges for Immersive Analytics based on use cases by the authors. We include 2 of these challenges *Combining Human and Computer Intelligence* and *Changing the Process of Analysis with Immersion* in our list of Grand Challenges in Table 1. The other 3 we feel are encompassed and extended by our more granular list.

## 2.2 State-of-the-Art in Immersive Analytics

**Empirical Studies:** While there are well-known limitations to displaying data in 3D on 2D screens (see [96, Chap. 6]), immersive environments potentially offer a better medium for both 3D data

display (through the use of head-tracked stereo, immersive navigation and natural interaction) and for 2D data display (by virtue of arbitrarily large 2D surfaces within an open interaction space). As discussed by Marriott et al. [89], the trade-offs of displaying data in immersive environments are not fully understood. They therefore called for studies to explore these principles and, in recent years, important new results on this matter have been published.

Kraus et al. [75] found that multi-dimensional clusters are easier to identify in VR than in a 2D desktop display, where dimensions must be split across a small-multiples view. Yang et al. [144] found that 3D globes are more effective for conveying distance and direction on world maps than 2D projections. Thus, there appears to be tangible benefit to immersive display when the data is inherently more than two-dimensional. Another study of immersive map visualisation by Yang et al. [143] found that immersive environments enable seamless transitions between 2D views that are optimal for visualising different aspects of the data. There have also been promising results in designing immersive visualisations for entirely abstract data, such as graphs or networks. Kwon et al. [76] found that immersive VR graph layouts allow faster decisions and fewer errors compared to their 2D counterparts.

A recent study investigated how larger groups collaboratively make sense of data in VR, especially focusing on 3D space use [79]. They found that users were able to perform sophisticated analysis in the environment, were comfortable collaborating via 3D visualisations, and were able to structure their virtual workspace to support collaboration. Another recent qualitative study by Lee et al. [78] found that immersive visualisations provide a *visceral* experience to engage users in data stories. A preliminary expert study by Batch et al. [10] found that analysts made more use of 3D space when presenting their data visualisations in immersive environments and used less space when creating and designing visualisations. The notion of space, distances, and spatial understanding has also been studied elsewhere [30, 70, 129].

Study results are now being distilled into design recommendations for immersive visualisations, some of these quite pragmatic, with a focus on working around technology limitations—especially in AR. Bach et al. [8] found limitations in the contemporary technology (Microsoft HoloLens V1) highlighting limitations in the field of view, resolution, stabilisation, and training requirements. Analysing the perception of visual variables (size, color, etc.) across VR, Desktop and AR environments, Whitlock et al. [138] offer guidelines for the use of visual variables in immersive environments. Yang et al. [141] derive guidelines for scalable navigation in immersive environments, exploring immersive equivalents of overview+detail and zooming as commonly used in desktop visualisation. They find that world-in-miniature and 3D zooming are complementary to physical navigation in immersive environments, but that they introduce overhead by requiring context switching between views. The results offer a nuanced *time-cost* model to predict for what tasks each navigation method will benefit.

Studying different layouts in 2D and 3D for small multiples data visualisation in immersive environments, Liu et al. [86] find trade-offs between the real estate offered by full wrap-around displays and problems caused by some information being behind and out of view of the user. Aside from visual perception, common immersive

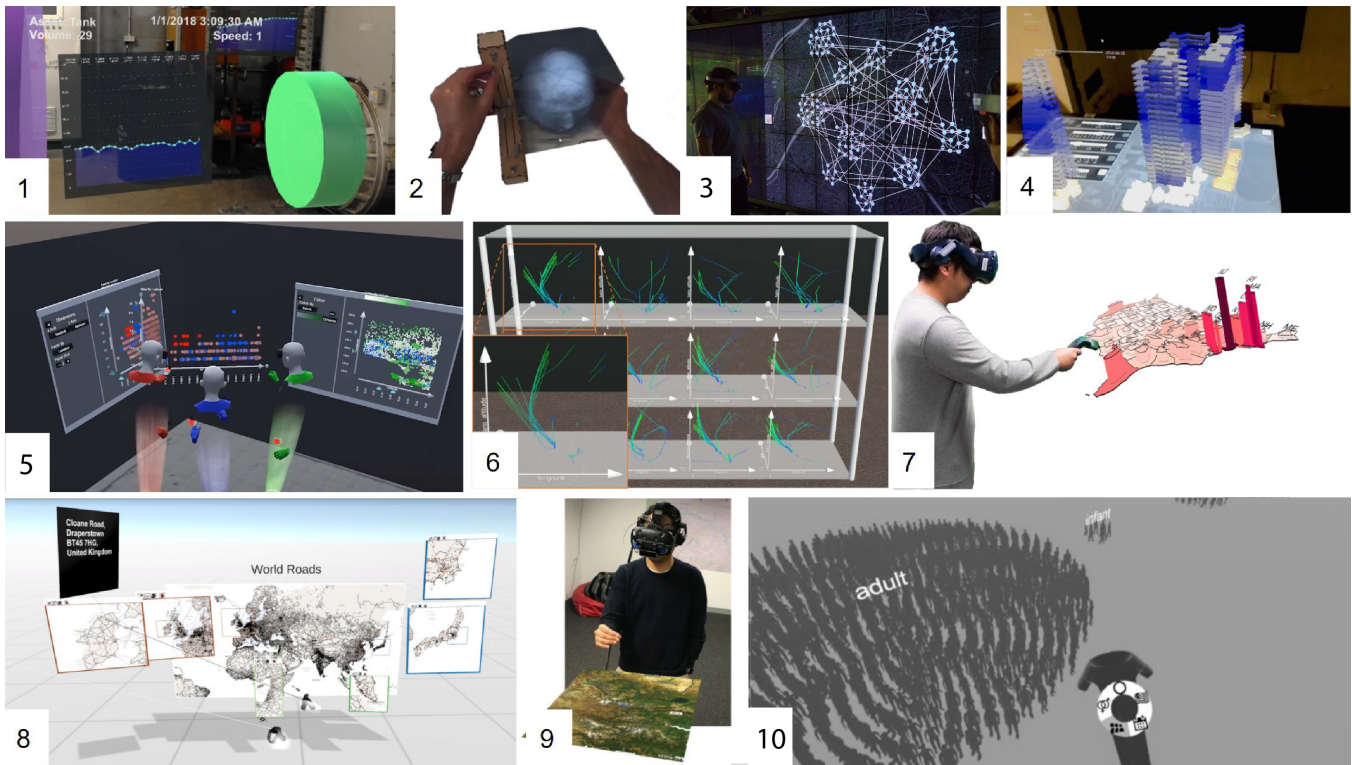
<sup>1</sup><https://shonan.nii.ac.jp/seminars/074>

<sup>2</sup><https://shonan.nii.ac.jp/seminars/131/>

<sup>3</sup><https://bdva.net/2018/index.php/introduction-to-iatk-an-immersive-visual-analytics-toolkit/>

<sup>4</sup><http://ieevis.org/year/2018/info/tutorials#IATK>





**Figure 1: Illustration of several recent Immersive Analytics systems:** (1) Corsican Twin [109], (2) the Embodied Axes [24] controller for precise interaction with 3D visualisations in AR, (3) AR personal navigation of networks on wall-size displays [72], (4) the UpLift system [46] mixes AR, a touch table and tracked tangibles for building energy analytics (image ©IEEE), (5) the FIESTA system for collaborative immersive analytics in VR [79], (6) a study of small-multiples in VR [86], (7) the Tilt Map [143] system for 3D Choropleth maps visualisation (image ©IEEE), (8) a multi-scale navigation system for map navigation in AR [114], (9) bare hand interactions [115] to navigate AR maps, and (10) immersive unit visualisation [71].

display technologies offer additional channels for data communication. For example, vibrotactile feedback provides an efficient means to convey internal cluster structures in 3D scatterplots of varying size [108].

In general, these promising results are beginning to evolve into guidelines for immersive data visualisation design, but there remains much further work before principles for Immersive Analytics are as evolved as those for traditional and well-studied 2D data visualisations.

**Interaction Techniques:** One of the often reported motivations for Immersive Analytics is the promise to perform embodied direct manipulation. For example, ImAxes [27] uses embodied interaction to assemble visualisations from the direct manipulation of 3D axes of data dimensions in 3D space. UpLift [46] uses tangibles on a touch table and the HoloLens to visualise and understand building energy on campuses. Filhio et al. [48] also built an embodied 3D visualisation of a space-time cube which uses embodied interaction to rotate, scale and query the visualisation. Controller-less techniques are also currently being investigated, including panning and zooming AR maps [115] or VR 3D graph node selections [67].

A known drawback of such manual interaction is that it can lead to fatigue, inducing the so-called “gorilla arm” effect. Recent

work investigates how tangible interaction can help counterbalance issues of fatigue due to 3D interaction in mid-air with VR controllers [25]. Filhio et al. [132] combined the tangibility of a physical desk tabletop with an immersive 3D scatterplot to make it suitable for extensive periods of data analysis and found that their setup was comparable to a traditional desktop setup. Cordeil et al. [24] built *Embodied Axes*, a 3D tangible controller that helps users perform more precise 3D selections in immersive 3D visualisations compared to traditional 6DOF mid-air controllers. These works establish preliminary steps towards making immersive environments more efficient and integrated into the user’s workspace for data visualisation, but more work needs to be done to bridge the performance gap between immersive techniques and traditional interfaces.

**Specific Application Areas:** Many Immersive Analytics applications explore problems in specific domains, including telemedicine [124], factory settings [109], IoT [13, 44], or geographic visualisation. Geographic visualisation includes techniques for map navigation [115], multi-scale navigation [114], space-time cubes [48], different representations of global geography [144], flow maps [142], and choropleth maps [143]. Many of these applications involve

situating data in the real environment, an area termed *situated analytics* [40], which has resulted in a design space for embedded data representations [140] and respective systems [109].

**Design, Authoring & Toolkits:** While most current research in Immersive Analytics focuses on exploratory and analytical interfaces, recent work has deployed design spaces and systems to inform authoring immersive environments beyond low-level programming in Unity, Unreal Engine, and AR-Toolkit. Conceptual design spaces have been proposed for developing devices and interaction techniques [25] and visualisations in AR [9]. DXR (2018) [123], Niwviw (2018) [145], IATK (2019) [26], VRIA (2020) [15], and U2Vis (2020) [111] are early general-purpose programming toolkits based on Unity (DXR, IATK) and web-technology (VRIA), providing pre-defined visualisation and glyphs, declarative programming, and previews for rapid prototyping, debugging, and customisation.

Whitlock et al. [139] provide FieldView, an open-source toolkit for immersive mobile application in the field with conditions different from lab settings such as low connectivity and screenspace. Similarly, Prouzeau et al. [109] present Corsican Twin, a tool for spatially embedded applications in industrial settings. No programming is required for systems such as MARVisT [21] to author glyphs in mixed reality and PapARVis Designer [22] to amend existing visualisations in the real world with holographic visual elements and extensions.

**Collaboration:** Supporting multiple users for sensemaking is one of the fundamental aspects of Immersive Analytics research [12]. Previous work investigated how users perform 3D network analyses in VR [29, 31]. Other work has also focused on group work in AR [119], including work with tangible touch tables [16]. This work allows researchers to better understand group dynamic in different data scenarios, and has served as validation of the effective use of immersive platforms for groups to work together.

**Commercial Products and Platforms:** Major tech companies such as Microsoft, Facebook, and HTC have been leading the development of immersive head-mounted displays. While many companies provide platforms for applications, there is no viable data visualisation software available from those companies. At the same time, startup companies have started commercialising immersive data visualisation applications, and few companies sell usable products. For example, Virtualitics<sup>5</sup> develops a desktop tool to build a visualisation that can then be viewed collaboratively in VR. Alaira<sup>6</sup> develops a wider set of visualisations that include graphs and 3D maps. However, naturally, it is challenging for these companies to adapt the most recent research and most advanced visual analytics techniques that can be found in commercial applications like Tableau<sup>7</sup>. Moreover, many techniques from research require additional work to be of commercial value and appeal to a large audience. Another likely challenge is onboarding novel users onto immersive applications, even if immersive hardware becomes increasingly affordable.

While this recent work has enumerated the promise of Immersive Analytics, it also sheds light on several potential challenges for successfully deploying Immersive Analytics tools into broader use contexts. We aim to enumerate these challenges to provide a

unified roadmap for innovation in Immersive Analytics.

### 3 METHODOLOGY

We elicited 17 grand challenges for Immersive Analytics in a collaborative workshop at CHI 2020 followed by multiple work sessions with international experts focusing on the four core themes emerging from the workshop discussions: Spatially Situated Data Visualisation, Interacting with Immersive Analytics Systems, Collaborative Analytics, and User Scenarios and Evaluation.

#### 3.1 Participants

Our preliminary workshops involved 28 international experts, out of which 24 joined to write this paper, with a combined expertise spanning over multiple areas: 3D interaction, accessibility, AR, cognitive science, collaboration, command selection, computer vision data visualisation, education, HCI, Immersive Analytics, input devices, interaction design, mathematics, mobile and wearable computing, multimodal interaction, perception, physics, qualitative methods, quantitative methods, shape changing interfaces, situated visualisation, spatial interaction, spatial UIs, storytelling, tangible UIs, ubiquitous computing, VR, and visual analytics. Participants came from around the globe (Europe: 7, North America: 19, Asia: 1, Oceania: 4). Most participants submitted a position paper to take part in the workshops, and all others have substantial experience in the Immersive Analytics field.

#### 3.2 Workshops Organisation

The process started with a multiple-day workshop, conducted virtually through Zoom due to the COVID-19 pandemic (Figure 2). The workshop spanned 2 weeks and included 4 sessions: one opening session, 2 asynchronous sessions, and a closing session.

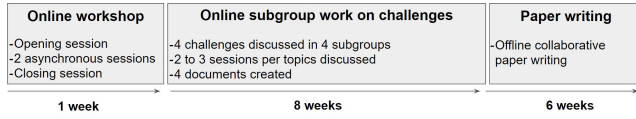
Prior to the workshop, organisers identified six relevant themes for discussion (Defining Productivity, Interaction Techniques, Collaborative Analysis, Users & Scenarios, Situated & Spatial Analytics, and Evaluation). Workshop participants were encouraged to contribute additional themes. Two of these themes were later combined (Users & Scenarios and Evaluation) and one was discarded (Defining Productivity). For the opening session (2 hours), each participant was asked to give a two-minute presentation using 2-3 slides that introduced themselves and any relevant work they would like to share. Then we conducted two asynchronous sessions (3 hours each) using a World Café [102] process to create subgroups and discuss these topics. The closing session (2 hours) was used to report and comment on notes from each subgroup.

After this initial workshop, we organised four sub-groups, corresponding to the 4 thematic areas, to carry out ideation and generative design sessions, with the goal of coming up with a set of 3-4 grand challenges for each thematic area. Note that most participants took part in various sub-groups, and that each sub-group included two organisers, who also attended other sub-groups, to ensure that the discussions among groups were not overlapping. Each subgroup met at least 3 times during this part of the process, which spanned 1-2 months. We summarise the resulting challenges derived by these meetings in the ensuing sections.

<sup>5</sup><https://www.virtualitics.com/>

<sup>6</sup><https://www.alaira.co.uk/>

<sup>7</sup><https://www.tableau.com/>



**Figure 2: The grand challenges process was initiated with a CHI 2020 workshop, followed by a series of sessions held over 2 months.**

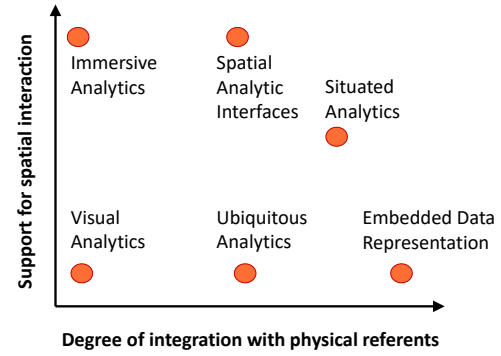
Topics	Challenges
SPATIALLY SITUATED DATA VISUALISATION	C1 Placing Visualisations Accurately in Space
	C2 Extracting and Representing Semantic Knowledge
	C3 Designing Guidelines for Spatially Situated Visualisation
	C4 Understanding Human Senses and Cognition in Situated Contexts
	C5 Applying Spatial Visualisation Ethically
INTERACTING WITH IMMERSIVE ANALYTICS SYSTEMS	C6 Exploiting Human Senses for Interactive Immersive Analytics
	C7 Enabling Multi-Sensory Feedback for Immersive Analytics
	C8 Supporting Transitions around Immersive Environments
	C9 Coping with Immersive Analytics Interaction Complexity
COLLABORATIVE ANALYTICS	C10 Supporting Behaviour with Collaborators
	C11 Overcoming Constraints of Reality
	C12 Supporting Cross Platform Collaboration
	C13 Integrating Current Collaboration Practice
USER SCENARIOS AND EVALUATION	C14 Assessing Collaborative Work
	C15 Defining Application Scenarios for Immersive Analytics
	C16 Understanding Users and Contexts for Evaluation of Immersive Analytics
	C17 Establishing an Evaluation Framework for Immersive Analytics
COMPLEMENTARY CHALLENGES (included from [125])	C18 Combining Human and Computer Intelligence
	C19 Changing the Process of Analysis with Immersion

**Table 1: Grand Challenges Overview. Complementary challenges are discussed elsewhere [125].**

## 4 SPATIALLY SITUATED DATA VISUALISATION

A very appealing aspect of immersive analytics is using wearable AR displays to visualise data within the world around us. By overlaying a visual representation on an object or location associated with the data's source, known as a *referent* [140], users may be made aware of useful spatial relationships in a data set—all while keeping their

### Spatially Situated Visualisation Continuum



**Figure 3: Various approaches can be coarsely placed on the spatially situated data visualisation continuum, by the degree to which they spatially integrate data encodings with physical referents, and by their support for spatial interaction.**

hands free during industrial work or other mobile tasks. However, the degree of integration between a data representation and referent can vary over a wide spectrum, many instances of which have been described in prior literature.

The concept of viewing information electronically in relevant spatial locations can be traced back to Fitzmaurice [49], who coined the term *Spatially Situated Information Spaces*. Their use of ‘palm-top’ computers was influenced by the contemporaneous concept of *Ubiquitous Computing* [137], which envisioned a shift toward computing activities blended into our daily activities. More recently, Irani and Elmqvist [37] introduced *Ubiquitous Analytics*, which links Ubiquitous Computing and Visual Analytics to conduct data analytics “in the wild” with available mobile technologies. A stronger link to Fitzmaurice’s ideas was drawn by Ens et al. [47] with *Spatial Analytic Interfaces*, which discussed how wearable AR and spatial interaction could be applied to support *in-situ* analytic tasks by registering information with the surrounding environment. Around the same time, ElSayed et al. [41] coined term *Situated Analytics* to express the spatial integration of data representations with a meaningful spatial referent. Willett et al. [140] make the difference between ubiquitous analytics and situated analytics more explicit: They distinguish *situated* data representations, which are located near their physical referent, from *embedded* ones, which are more tightly integrated with the referent.

Several challenges result from the practical application of these various approaches (Fig.3), from the differences of design implications between them, and from how they affect our relationships with physical space.

### C1: Placing Visualisations Accurately in Space

Placing a digital visualisation at a desired position in the physical world is fundamental to spatially situated visualisation. While this kind of physical registration is often trivial when situating screen-based or physical data representations, it represents a serious challenge for immersive AR tools. Stable spatial registration



is essential since virtual objects should stay in the same position and orientation unless they are intentionally manipulated [116]. To achieve a stable spatial registration, an AR device (either an HMD or a mobile device) has to know its 3D position and rotation in the environment, and the spatial relationship between itself, the virtual objects and the physical surroundings.

Major AR platforms all have their own implementations of spatial registration, including Microsoft's HoloLens [94], Apple's ARKit [3], and Google's ARCore [55]. Existing platforms focus on using computer vision to build a map of the surrounding environment and locate the device and virtual objects within the environment using simultaneous localisation and mapping (SLAM). However, there are still several unsolved problems with this approach for immersive analytics.

First, many applications only consider scenes at room-scale. However, there are cases where much larger scales of spatial information are required. For example, Pokémon GO [97] utilises the whole world as its virtual space; Google Map AR uses virtual indicators to help users navigate. More and more applications require reference data at a large scale. In these applications, GPS data can provide coarse spatial information, but it is not precise enough to provide a stable spatial registration. A mechanism such as the one of Arth et al. [4] is needed that can take advantage of GPS data at a larger spatial scale as well as precise computer vision and other sensor data. Recent ultra-precise GPS methods allow sub-centimeter location accuracy, while indoor environments may take advantage of recent Ultra-Wideband hardware.

Second, we need to know not only the position of the viewer, but also spatial properties of the referents. Most existing solutions compute the spatial information on the fly. We can potentially get more accurate data from existing sources, such as floor plans and building information modelling (BIM) [109], but these data sources usually lack details that could be obtained from computer vision, such as damage from recent disasters or positions of transient objects like people or furnishings. In some cases, only existing spatial data sources are available. For example, a designer may remotely arrange the furniture for homes that she has not visited. A mechanism is needed to optimise data availability and quality from various data sources.

## C2: Extracting and Representing Semantic Knowledge

Placing data representations with precision relative to referents requires the ability to recognise and track relevant objects. In addition, automating the behaviour of data visualisations, providing context-aware behaviour, and automating layouts requires *scene understanding* [1, 83]—the ability to understand objects in the context of their surroundings, including dynamic behaviours and functional relationships.

While research in this area is ongoing, situated visualisation faces further challenges, for instance, providing robust input from existing wearable sensors to provide context awareness [60]. Moreover, the display of information based on spatial understanding must be presented with accurate spatial registration to be useful in practice.

Providing designers with the ability to easily author data visualisations will further require the ability to represent and store complex semantic information at a human-understandable level. In the past decade of evolution of online information systems, 2 approaches have prevailed. Hand-crafted ontologies [99] work for highly structured domains, such as engineering or law. Less structured domains, such as traffic management, social computing, or entertainment, are better served by mining big data collections with Bayesian statistics to extract common patterns. In either case, these approaches can be applied to situated analytics as well, given that they can be considered online information systems with added contextual from the physical locations of users and referents. However, securing and correctly classifying such context in a (typically mobile and resource-constrained) setting is inherently challenging.

## C3: Designing Guidelines for Spatially Situated Visualisation

Much of the prior work in situated visualisation is motivated by the assumption that increasing the degree of real-virtual integration will increase the user's ability to understand data or make better decisions. For example, one might assume that an embedded visualisation that overlays colour-coded data directly on a referent object (e.g., price data overlaid on the shelf holding a product or temperature of a boiler on the exterior of a water tank) provides a more intuitive visualisation than a traditional 2D chart situated next to an object. Either of these options would, in turn, be preferable to a visualisation viewed on the screen of a tablet while standing next to the object. However, there are too few controlled studies on the relative benefits of spatially situated visualisations to truly understand these distinctions.

When deciding how tightly to integrate data encodings, we might assume there is an inherent tradeoff between intuitiveness, leading to immediacy of understanding, and degree of 'information bandwidth' [136], which may impact the potential scope of understanding. For instance, layering many visualisations on or around equipment in a physical plant may make valuable information immediately available, but visual encodings may be limited to those that facilitate preattentive visual processing [61]. In contrast, a situated visualisation abstracted from the physical form may be able to include additional dimensions, such as temporal data [109], but may be slower to process cognitively.

It is important to understand how different representations impact users' ability to discern information from the physical surroundings. Currently, many research questions in this area remain unanswered. How do we determine the relative importance of objects in the physical world to know what should not be occluded? When dealing with multiple related visualisations, what is the optimal layout to support a user's tasks? These issues become exponentially more complex when we consider dynamic real-world environments, which constantly change, contain moving people, or expose dangerous equipment. Additional complicating factors include variation in user 3D perception capabilities and known hardware limitations such as vergence-accommodation conflict that may introduce variations in where people perceive data relative to the physical space. Dedicated studies are needed to understand the implications of placing visualisations in users' environments.



With better understanding, we will be able to produce a detailed set of guidelines for designing such visualisations under a complex array of different tasks and circumstances. This may also require developing robust evaluation methods for data representations and automatically generated layouts.

#### **C4: Understanding Human Perception and Cognition in Situated Contexts**

Effectively distributing data visualisations in our physical environments will first require us to gain a better understanding of how the human analyst perceives, interprets, and processes information. In particular, there needs to be substantial study of how analysts interact with data in spatial tasks and contexts. While there has been a great deal of study of cognitive processes during interaction with desktop interfaces [17, 101, 122], there has yet been little direct study of interaction with AR, particularly with data visualisation and analysis tasks. It is important to understand how the added spatial context affects a user's ability to interpret information. For instance, what are the specific cognitive benefits of a spatial association between data and a physical referent? How are such benefits impaired by ever-present real-world distractions in dynamic settings? What are the costs of processing information across both digital displays and physical objects [36, 53]? Can we leverage human abilities for efficient visual processing [136] (perhaps through embedded visualisations) and distributed cognition [65] (by distributing cognitive aids in strategic physical locations)? How can different strategies for integrating information with the physical environment be used to reduce working memory and cognitive load? What are the limitations of human attention, and how do we avoid exceeding these when adding sensory stimulus into dynamic environments?

#### **C5: Applying Spatial Visualisation Ethically**

Concerns over tracking and collecting personal user data, such as shopping history, information browsing habits, device usage, and physical location are already prevalent with current smartphone devices [73]. These concerns have potential to become much more substantial with immersive devices, which may provide access to more detailed data about our activities, such as specific head pose, eye gaze, and indoor location. In the future, VR displays may contain additional physiological sensors, such as EMG, EEG, GSV, etc., which reveal our responses to stimuli and even our thoughts. Some of this physiological information is already captured by smart watches, and the Amazon Halo went further by detecting emotions using the tone of voice [112].

This increased access to intimate information has raised concerns. For instance, many VR users reject the recent decision by Facebook to require users to sign in when using Oculus devices [112]. When considering data analytics, such concerns must be addressed to alleviate ethical and proprietary concerns over access to sensitive data by providing a pipeline that does not expose data to collection. Situated visualisation has the potential to expose sensitive relationships between data and referent objects or specific locations. These issues could be alleviated by the development of system software that prevent detailed data needed for device functionality from being passed on to external sources [130].

Other concerns arise with collaborative applications, where robust privacy settings are needed to prevent sensitive spatial data from being viewed in the wrong context or by collaborators without granted permissions [56]. Further design considerations will need to be developed for users of situated visualisation applications to keep them safe from potential dangers that may arise due to distraction. Social considerations also may arise from how application use affects others in the user's vicinity [64]. Supporting safe and social applications will require integration of contextual awareness [57] with adaptive systems [85].

### **5 INTERACTING WITH IMMERSIVE ANALYTICS SYSTEMS**

Interacting with Immersive Analytics systems is uniquely challenging in part because of a combination of novel, multimodal input and output technologies and demanding complex use cases. Consequently, challenges arise regarding how to make use of human perception, cognition and interaction capabilities, how to support transitions around immersive environments, how to cope with the high complexity of immersive interaction for data analysis, and how to design spatial and multi-sensory feedback.

#### **C6: Exploiting Human Senses for Interactive Immersive Analytics**

The need to better understand human spatial perception and cognition is a grand challenge across multiple fields. For Immersive Analytics, it inspires a key challenge in interaction design: How can designers best exploit human senses for efficient Immersive Analytics? Given the prevalence of multimodal interaction in Immersive Analytics, understanding human senses can allow visualisations to better map interaction modalities to the most appropriate human sense. Visuals provide information for our sense of sight. Sound is the next easiest to support with existing technologies, followed by touch. Immersive systems usually have spatial environments which the user can freely traverse. Such environments can be taken advantage of by both sound and touch. Objects emitting sound within the environment may benefit from spatialised audio, assisting users in finding the object's location. Touch can assist us by allowing us to detect objects outside our field of view; alerting us of their existence without having to directly look at them.

A related challenge is how to make our systems accessible to people who cannot use some of these channels, such as people with visual impairments [147]. For example, tactile components in visual analytics have been used to support visually impaired analysts [92]. Research into actuated displays [50, 82] offer a promising direction for visually augmented tactile dynamic immersive experiences for visual analytics.

Finally, Immersive Analytics needs to consider physical exertion: gestural input, spatial interaction, and physical navigation are all physically demanding. Research into the physical interactions needed for immersive analytics, especially in virtual environments, is often limited due to users suffering from increasing feelings of simulator sickness or discomfort with lengthy use. Duration limitations are often due to headache, nausea, dizziness, motion sickness [52, 131], eyestrain [74], heat from usage (battery packs, displays,

additional layers of fabric), muscle fatigue (neck/shoulders), pressure marks due to a HMD strapped and pressed into one's face, and, most notoriously, "gorilla arm" due to physical exertion during interactions [63]. A critical goal for future Immersive Analytics research is to design an immersive system that allows prolonged usage for users interacting in ways standard to data analytics.

### C7: Enabling Multi-Sensory Feedback for Immersive Analytics

A challenge complementary to multimodal interaction is multi-sensory feedback. While multi-sensory data representation in Immersive Analytics has been previously discussed [91], there is a need to also consider multi-sensory output as feedback for input. Of the 5 senses (sight, sound, touch, smell, and taste), electronic devices usually are able to provide for sight and sound, though recent advances may facilitate other senses [103, 110, 133]. Mobile devices and immersive controllers have some limited capabilities for touch feedback. The remaining senses, smell and taste, are the hardest to be able to reproduce on demand. One of the earliest multi-sensory immersive systems was built in the 1950's, the Sensorama [62]. There have recently been research efforts into altering our perception of taste through smell in VR [84].

Arguably audio is the closest of the 5 senses to readily providing us with a fully immersive sensory experience using commodity technologies. Headphones (or earbuds) with built in noise cancellation and capability for spatialized audio would, in theory, be able to fully block out the real world and allow us to only hear the immersive environment. However, this leads to an interesting question: Should the real world be blocked out? Emulating our senses helps provide a sense of immersion and allows us to continue to utilise them as we are familiar (for example, locating an object based on sound alone). But the challenge with audio is determining when to break away from emulating the real by altering the audio to enhance our experience.

The capability to provide touch is in a juvenile state for common commodity devices. Texture is something that cannot be easily conveyed without specialised hardware. From this point of view, there are many directions in which touch can be improved: better location coverage, texture, proactive (touching something) versus reactive (something touching the user), resistance, and other variations, like temperature. However, unless a brain-to-computer interface alternative is developed, touch will need physical emulation through specialised, worn equipment. In a future with advanced haptic devices, the grand challenge for Immersive Analytics would become determining a standardised set of equipment to provide the ideal minimum set of functionalities for each of our senses. Upon reaching this point, the challenge becomes identifying when to break away from realistic emulation, similar to audio.

### C8: Supporting Transitions around Immersive Environments

Immersive Analytics users must cope with multiple kinds of transitions, such as the transition between a mostly seated work environment and one that requires more physical involvement, the transition from using desktops (where most users have expertise) to Immersive Analytics (which may be novel and unfamiliar) [58, 135],

or the transition between input devices as the user switches between conventional and Immersive Analytics systems throughout the analysis workflow [121]. While novice-to-expert transitions are well-studied in the literature [23], Immersive Analytics brings about new, far more complex transitions which can affect interaction fluidity [38].

To solve these challenges, future systems might aim to lower entry barriers to Immersive Analytics interaction. One promising possibility is to combine established interfaces, like keyboard, mouse or tablet input, with immersive HMDs [11, 14, 54, 58, 135]. This is closely related to the question of discoverability: many "natural" interaction techniques used in Immersive Analytics, including gestures, speech, and tangible tokens, are not obvious to users [98], which risks hiding possible actions from them. Working towards a unified interaction vocabulary can help make these transitions easier. The goal of this simplification is to reduce the learning curve for Immersive Analytics users and to better exploit existing expertise.

### C9: Coping with Immersive Analytics Interaction Complexity

Immersive Analytics interaction is inherently multimodal and multiview, leading to rich and complex interaction scenarios. In contrast to many prior immersive systems, Immersive Analytics needs to support a multitude of different, often complex analysis tasks; simple direct manipulation techniques may not be sufficient. For instance, annotation is a key task in most analysis workflows, leaving room to investigate the use and productivity of text entry modalities in Immersive Analytics [33].

There are a variety of interaction technologies: different display technologies (HMD, tablet, projection) will probably need different input devices (6DOF controller, 3DOF controller, speech, gesture, eye gaze, head orientation, tangibles). However, prototyping such device combinations is difficult [104], and many of these interaction modalities are not mature enough to allow a systematic use for analytic tasks. For instance, on-body interaction has received much attention [113, 120, 146], but previous work has mostly explored the use of such modalities for simple tasks. Understanding the relation between tasks and technologies will allow Immersive Analytics systems to exploit the rich interactive techniques of immersive systems to conduct analysis tasks as efficiently as on regular desktop environments.

## 6 COLLABORATIVE ANALYTICS

The possibility to facilitate collaboration, either remotely (using approaches like AR and VR) or colocated (in contexts like CAVEs), is a key benefit of Immersive Analytics systems. In this section, we describe challenges related to how people collaborate using such systems. They focus on the behaviour of users with other collaborators in this context, on the constraints of reality, the use of different platforms, and more generally on the integration of the current practice and the assessment of the collaboration.

### C10: Supporting Behaviour with Collaborators

While different tools exist to meet and work collaboratively using immersive technologies, such capabilities are still relatively

new for a large proportion of users. One challenge will be to actually teach users to collaborate with such technologies. It means, at first, providing them with a good understanding about how to perform specific tasks with Immersive Analytics (including how to share views or data and how to control permissions for virtual objects), and second providing them with a good understanding of the different ways they can communicate with others (can they use hand gestures, head movement, is the sound of their voice lowering with distance?). Finally, users should understand the technical constraints of the current system (latency, lack of facial expression, etc.). In an ideal system, these capabilities should be easily discoverable by users while starting their collaboration using affordances (and the appropriate signifiers). For instance, the use of hand models to replace the more classic controllers in some current VR tools allows users to infer that they can actually perform a (sometimes limited) set of hand gestures.

Another crucial point for future research is to learn to establish communication between users for various collaboration forms [69]. In the context of data analytics, different ways of communicating about data can be identified: (1) free-form communication between data analysts when they make sense of the data together and (2) more formal communication when an analyst presents the data to a given audience.

One challenge in Collaborative Immersive Analytics is to provide platforms that integrate communication scenarios in a transparent way. For example, a group of analysts should be able to meet in a VR space that allows them to communicate freely with each other when making sense of data. Freedom of movement, annotation, and oral communication is crucial when building meaningful visualisations as a group. Conversely, when a group of analysts join a VR space to follow a data presentation, the system should limit the interaction of the attendees (for example, the avatar of an audience should not be allowed to go to the presenter's place, audio communication should be limited, etc.). The type of immersive technology plays an important role in this context. If users meet in a CAVE-style environment, their behavior cannot be constrained as much as it could be in a VR platform.

Finally, it is important to understand how users react to the different forms of embodiment of their collaborators. Such embodiment can be fully physical in a colocated settings (like CAVEs) and or using avatar in remote settings (as with HMDs). In the latter, the degree of embodiment has been shown influence how people socially behave. On a remote setting with tabletops, Doucette et al. showed that a higher degree of visual embodiment led to a better workspace awareness and more awkwardness when people cross embodiments [32]. Overall, there are still interesting research questions to tackle to support effective collaboration: What affordances can show users how to collaborate? What collaboration cues can support different collaboration styles and transitions between those styles? How can these cues be used to constrain users' action in support of the task? What would be the impact on collaboration of the different forms of embodiment available in different platforms?

## C11: Overcoming Constraints of Reality

Using VR technology to implement collaborative virtual environments (CVEs) allows for co-presence [93] and communication using

not only speech and potentially video, but also gestures, posture [127], and even facial expressions [19] for geographically dislocated users. All these communication channels are available naturally in real world co-located collaboration, but have to be artificially enabled in a CVE.

The fidelity of the remote user representation is highly dependent on the tracking technology (head+input devices, gestures captured from input devices, eye tracking, and tailored prototypes [90]). Not all participants will have the same equipment available and thus may be represented differently, leading to asymmetries in interaction and communication.

Although we still face many technical challenges implementing a fully articulated user representation, VR can provide means to enhance communication and improve collaboration. Pointing visualised by ray representations allows for exact indication of an area or point of interest. Eye gaze or the view frustum of the remote user could be displayed to highlight the awareness area [107]. Immersive Analytics uniquely affords sharing 3D datasets and discussing them in the same CVE, as if they are physically available in the same space.

Several research questions still need to be explored: How can systems manage the asymmetries of collaboration cues due to the differences of material used? What constraints in reality could be overcome by immersive technology? Could more efficient workspace awareness techniques lead to more efficient collaboration than working face-to-face? Although current systems like Spatial.io<sup>8</sup> or Mozilla Hubs<sup>9</sup> allow for loading data sets and support multiple display types and input modalities, they still only provide a very basic implementation of collaboration and visualisation support, as it would required for collaborative Immersive Analytics.

## C12: Supporting Cross Platform Collaboration

Collaboration often entails a diverse group of participants all working together towards a common goal. However, these participants often do not share the same space, technology, or capabilities. Users wishing to collaborate with Immersive Analytics technologies should not be limited to only collaborating with users of the same Immersive Analytics technologies. A key opportunity for future Immersive Analytics collaborative research is to explore the space of cross-platform collaboration. Such spaces bring a multitude of opportunities. For example, someone with a VR headset could collaborate with a group of people in a CAVE, or more simply, someone with a desktop with someone with a VR headset. Such collaboration could be useful in cases where participants have different roles [134] or where users have to perform different tasks that need different perspectives [68].

Differences in display type raise many interesting questions. Both the display dimensionality (3D for VR/AR headset and CAVE, but 2D for Wall displays or desktops) and the modalities of interaction (6 Degrees of Freedom controllers, mouse, keyboard, multi-touch, etc.) can vary significantly. Is it better to provide the same environments to everyone (in favor of common ground), or to adapt the visualisations to the characteristics of the display for each user? In the latter case, how would a workspace provide awareness to

<sup>8</sup><https://spatial.io/>

<sup>9</sup><https://hubs.mozilla.com/>



each user and, more generally, allow appropriate communication, using deictic gestures?

An interesting use case in which to study such questions is education. Imagine students coming to class joined by others remotely from their home, using desktops or VR.

### C13: Integrating Current Collaboration Practice

Immersive collaboration systems must cognitively compete with established collaboration practices. It is the norm to collaborate without immersive systems, be it face-to-face in a meeting room or at a distance with video conferencing. Using immersive systems is novel and uncommon, if used at all. This is due in part to hardware constraints like availability, cost, and space. Although distance formats are becoming increasingly common, their productivity is still measured against face-to-face formats. Immersive systems have a few peculiarities that allow designing for local, distance, or hybrid collaboration.

To support, enhance, or emulate face-to-face meeting spaces, some common information actions must be considered: content contribution, organization of content, enabling others to review and correct, taking notes or annotating directly, and recording to allow later review or asynchronous participation [81]. This list does not take into account features necessary to support awareness of others or synchronization between participants. In support of local collaboration, CAVE developers have noted that their design has shifted from being a system within the room to being the entire room. Their goal is a war room [88] to support co-located collaboration [128], but they must fall back on other formats (such as video conferencing) to support distance collaborators. In this scenario, participants are capable of hosting a traditional meeting and taking advantage of immersive features on demand. The system is a complementary component of the meeting, which could have otherwise still occurred without the system. In order for immersive systems to be the main component of the meeting, they must provide not only features to support traditional environments but capabilities “beyond being there” [66].

Distance collaboration offers the greatest opportunities for Immersive Analytics, but also starts with the largest hurdles to overcome. The primary problem for distance collaboration is a question of how much is expected of an immersive system. Should the immersive system fully support a collaboration session from start to end or only part? It is possible for immersive systems to be used for phases or parts of collaboration rather than the entire session. But is it practical? Consider how different system swapping is from software swapping. Modern meetings often involve frequent software swapping. An example scenario is checking one’s email to get a link allowing access to the video conferencing. During the meeting someone shares a PDF for download to allow private viewing and later the team works on a shared online document. Swapping between these 4 applications (email, video, PDF, and shared document) can all be done from one system and is significantly different from swapping between 4 different machines throughout a meeting. Immersive systems intending to fully supporting collaboration sessions must design and create features to emulate traditional collaboration on top of addressing problems that arise from distance collaboration [100], which modern video conferencing software

applications are still trying to address. These problems are further complicated by the 3D nature of immersive systems and potential environment disparity between users, both virtual and physical. Immersive systems must support the full workflow of current practices, if collaboration sessions are to be conducted without interruptions or device switching. Reflecting back to the previously-mentioned information actions, immersive systems will need to break away from focusing on only its strengths and consider the integration of non-3D aspects for the sake of productivity, for example, note taking and document editing. It should be noted that there are different types of meetings (presentation, brainstorming, design review, etc.) that define intention and purpose behind collaboration. Identifying and implementing a core set of features to target a specific type of meeting (or user group) will be critical in convincing users to adopt it as part of their current practices.

This challenge leads to several research questions, including: How much should systems support, enhance, emulate, or deviate from current collaboration practices in immersive environments? How systems can integrate both colocated and remote users, and thus support different types of hybrid collaborations? How much of the collaborative session should be supported by the immersive system?

### C14: Assessing Collaborative Work

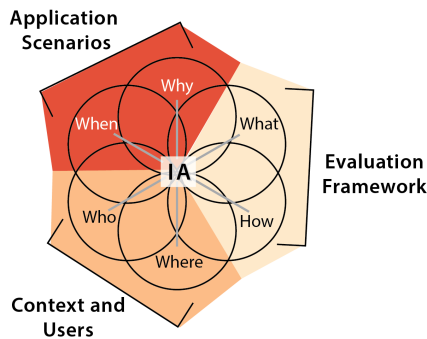
As new collaborative Immersive Analytics systems are designed, one challenge that emerges is how to assess the role the system plays in facilitating productive collaboration. Collaborative work is difficult to evaluate as there are many variables to consider. Collaborative Immersive Analytics systems need to support both taskwork and teamwork [77, 105] as the outcome of the task and the dynamics of collaboration are important. Therefore, evaluation frameworks must leverage both qualitative and quantitative measures to assess the quality and effectiveness of collaboration while using Immersive Analytics systems.

While some parallels between in-person collaborative work and collaboration in virtual environments exist, further research is needed to account for the differences that virtual environments introduce. When doing group work in an immersive environment, factors that could affect collaboration not present in colocated group work include device asymmetry (some users wearing a wireless or tethered VR headset, while others joining on desktop or mobile). This asymmetry could create a division in the ways specific members can participate in the collaboration, how communication and interaction cues are represented, and how collaboration can be observed in field and lab studies. Further research is needed to develop evaluation frameworks that account for these differences, so that researchers can better compare new collaborative systems to existing ones to inform the design of future systems.

## 7 USER SCENARIOS AND EVALUATION

In our discussions, identifying suitable scenarios for Immersive Analytics and evaluating them accordingly has been identified as a grand challenge. Specifically, we define 3 grand challenges as illustrated in Fig. 4. In “Defining Application Scenarios for Immersive Analytics,” we address the challenge of identifying *why* certain scenarios lend themselves to immersive analytics, while others may





**Figure 4: Overview of the “User Scenarios and Evaluation” grand challenges. These challenges collectively consider how users and applications shape assessment in Immersive Analytics (IA) systems.**

not. We emphasise the need to develop recommendations as to *when* in the overall analysis process Immersive Analytics would be best placed. The “Understanding Users and Contexts” challenge addresses the questions surrounding *who* the users of Immersive Analytics systems are and *where* they perform their work. Finally, challenges in designing evaluative studies illuminate the need for “Establishing an Evaluation Framework for Immersive Analytics” that we consider instrumental for defining *what* attributes of Immersive Analytics systems we need to consider to evaluate system performance and *how* these attributes can be measured. While each challenge addresses some specific questions as posed above, we acknowledge that there is a certain degree of overlap between them.

### C15: Defining Application Scenarios for Immersive Analytics

The brief survey in Section 2.2 as well as other existing surveys [51] highlight the broad range of application areas in which Immersive Analytics has been used. Past work reports both success as well as failure stories. As an Immersive Analytics research community, we know that not all domains or problems lend themselves to Immersive Analytics approaches or technologies nor do they benefit equally from the unique affordances of Immersive Analytics. We argue that, in order for Immersive Analytics to become a productive means of performing data analysis, we (collectively as a research and end user community) need to identify those scenarios and applications that benefit from Immersive Analytics. We need to be able to answer questions such as: Why do specific scenarios benefit from Immersive Analytics while others do not? What are the key attributes of specific applications that make Immersive Analytics useful? When in the overall analytics workflow can we best integrate Immersive Analytics?

By creating a set of recommendations and guidelines for when Immersive Analytics can benefit a target problem, different domain communities may be able to use Immersive Analytics more successfully. Determining the tasks and scenarios that Immersive Analytics tools can specifically enhance will facilitate engagement of users in the creation and use of Immersive Analytics systems.

These components can scaffold conversations and design processes that holistically tailor analytics solutions to the characteristics of a target problem. This can lead to greater usability of Immersive Analytics tools and greater adoption of solutions that maximize benefits to users.

### C16: Understanding Users and Contexts for Evaluation of Immersive Analytics

When designing user studies, researchers must take into consideration who the target users for the system are, where they work, and what kind of tasks they are likely to pursue [118]. While these considerations seem intuitive and are well-known in the HCI community, too often we see studies in the Immersive Analytics community that limit themselves to short experiments with participants that are easily accessible, such as students from a university or colleagues from work [18]. In doing so, we gain limited insight into the actual productivity and user experience of Immersive Analytics in real-world problems solved by domain experts. Furthermore, given the complexity of Immersive Analytics systems, we may observe a range of user experiences that are amplified as compared to conventional analytics systems such as nausea, fatigue, and physical discomfort. Through their novelty, we may observe short term bias towards over-acceptance of these systems as they are perceived exciting and fun to use. Open research questions that we consider important in this context include: What are the attributes of end users who are accepting of Immersive Analytics systems? To what degree is acceptance of Immersive Analytics dependent on novelty bias? What are the long term user experience effects of using Immersive Analytics systems?

To address these questions, we need to provide means for both short- and long-term assessment of deployed Immersive Analytics technologies to accommodate effects like novelty bias, learning effects, and changing acceptance of immersive technologies across a range of scenarios. Formal protocols should be established that clearly define criteria for participants’ selection and assessment. Measuring performance across time may also call for establishing a user community. A formalised, established community would allow researchers to elicit user feedback on the usability and productivity of the emerging technology (translational computer science) with both domain experts and with experts familiar with the technologies to help mitigate confounding effects such as novelty bias.

### C17: Establishing an Evaluation Framework for Immersive Analytics

Evaluating HCI systems with the aim of drawing strong conclusions on user experience and performance is difficult under the best of conditions. In Immersive Analytics, we deal with specific challenges, some of which are outlined above, including novelty bias, learning effects, and uncertainty about application scenarios. Being able to measure the effects of these challenges is instrumental in understanding the value of Immersive Analytics systems, but what are the most suitable methods and metrics to quantify these effects? How do we deal with the curse of dimensionality in these studies, given the wide range of factors to assess in these complex systems? We propose that the Immersive Analytics research community needs to establish a grounded framework [80] of methods

and procedures that clearly specify what aspects of Immersive Analytics need to be assessed and how these can be measured using suitable metrics. This framework should include physiological measures to capture experiences, such as fatigue, arousal, etc. Other fields, such as ubiquitous computing [117], have formulated such frameworks to help researchers identify an area of interest, the concepts associated with that area, and the metrics employed to evaluate such concepts [39, 77]. While the specifics of evaluation techniques and metrics may vary depending on target scenarios and systems, a common framework can offer a starting point for study design that may enable comparison across studies. The framework may also provide perspectives on when specific research questions require a more focused, controlled study and when productivity and usability evaluation needs an “in the wild” study.

## 8 DISCUSSION AND CONCLUSION

In this paper, we describe 17 grand challenges facing Immersive Analytics researchers. Although current contributions to the field are already demonstrating the benefits of Immersive Analytics, we believe finding solutions to these challenges will help Immersive Analytics systems to reach their full potential.

Our challenges emerged from multiple sessions with a group of international experts in Immersive Analytics. We identified 4 themes within Immersive Analytics (Spatially Situated Data Visualisation, Interacting with Immersive Analytics Systems, Collaborative Analytics, and User Scenarios and Evaluation), comprising 17 grand challenges. We acknowledge that some of these challenges will be difficult to solve, as they are confronted with inherent limitations of digital immersion, human cognition or immersive technologies. However, our paper focuses on the scientific challenges of Immersive Analytics, leaving aside other important considerations such as commercialisation, hacking and security, policy-making, or social inclusion. Some considerations such as privacy and access to technology were briefly discussed and further work will be needed to both better understand and tackle those challenges.

The set of design challenges we discuss are both technically and conceptually complex, and addressing them will require technical, epistemological, and social contributions from across a range of research communities. Challenges like designing guidelines for spatially situated visualizations (C3) depend on knowledge specific to the visualisation community and represent extensions or reframings of ongoing and important challenges in visualisation research. Others, such as extracting semantic knowledge from real world environments (C2) and reliably integrating visualisations into real-world settings (C1) are more technical in nature and call for contributions from adjacent communities including computer vision and sensor integration. Finally, challenges related to collaboration (C10-14), user scenarios (C15,16), and evaluation (C4, C17) share links to work in social computing and human-computer interaction more broadly. As a result, addressing these challenges requires interdisciplinary collaboration that connects Immersive Analytics researchers with experts well-suited to confront these broader technical and social concerns. Such links will allow Immersive Analytics applications to benefit from active research in these adjacent areas, while also contributing compelling use cases to motivate new sensing and collaboration techniques.

We hope this paper will bring the growing Immersive Analytics community together, open new discussions, inform common research goals, help onboard researchers new to Immersive Analytics, and provide a coherent view to outside stakeholders, such as companies and funding agencies. Immersive Analytics offers tremendous potential to extend and enhance our abilities to make sense of and communicate through data. Addressing the challenges laid forth here will enable us to realize this potential and introduce innovative advancements in this innovative, interdisciplinary field.

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