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# Immersive Analytics with Augmented Reality in Meteorology: An Exploratory Study on Ontology and Linked Data

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## Abstract

Although Augmented Reality (AR) has been extensively studied in supporting Immersive Analytics (IA), there are still many challenges in visualising and interacting with big and complex datasets. To deal with these datasets, most AR applications utilise NoSQL databases for storing and querying data, especially for managing large volumes of unstructured or semi-structured data. However, NoSQL databases have limitations in their reasoning and inference capabilities, which can result in insufficient support for certain types of queries. To fill this gap, we aim to explore and evaluate whether an intelligent approach based on ontology and linked data can facilitate visual analytics tasks with big datasets on AR interface. We designed and implemented a prototype of this method for meteorological data analytics. An experiment was conducted to evaluate the use of a semantic database with linked data compared to a conventional approach in an AR-based immersive analytics system. The results significantly highlight the performance of semantic approach in helping the users analysing meteorological datasets and their subjective appreciation in working with the AR interface, which is enhanced with ontology and linked data.

**Keywords:** Immersive Analytics, Augmented Reality, Ontology, Linked Data, Meteorology

# 1 Introduction

Advances in Augmented Reality (AR) and Virtual Reality (VR) have resulted in the emergence of Immersive Analytics (IA), a domain combining immersive technologies and Visual Analytics. This approach emphasises on analytical reasoning and decision making process through the “human-in-the-loop” approach (Thomas and Cook 2006). Following this paradigm, Immersive Analytics (IA) takes advantages of immersive systems to allow users to be immersed in the data-world for better data analytics performance (Chandler et al. 2015). Indeed, by including the users in the analytics processes, human-centred IA integrates interactive and immersive visualisation into automated analysis techniques in order to actively employ the users’ perceptual and cognitive capabilities toward data analysis tasks. The users’ active involvement can, in turn, help build better information models for extracting insights from data.

Big data is at the heart of this emerging IA field. The sheer volume of the data and its heterogeneity are two of many challenges that IA has to deal with to make the data accessible and interactive within the reach of the users. Most AR applications use NoSQL databases to store and query data (Rodriguez and Huang 2017; Shah et al. 2022; Naticchia et al. 2019), or to handle large volumes of unstructured or semi-structured data (Amirian et al. 2015; Seipel et al. 2019; Khan and Nandi 2021). However, NoSQL databases are limited in terms of reasoning and inference capabilities, therefore, may not support some range of queries. One approach to help reduce the complexity of the datasets and to accelerate the analytical reasoning process is to rely on the previous knowledge of the related domain(s) in the form of ontology and linked data. Essentially, an ontology is defined by Gruber (1993) as “a specification of a representational vocabulary for a shared domain of discourse - definitions of classes, relations, functions, and other objects”. In semantic web technologies, ontologies are used to help in the comprehension and manipulation of data. By linking structured data, linked data can enhance its utility through semantic queries (Bizer et al. 2011). Despite the fact that ontology and linked data are field-dependent, once the domain knowledge has been formulated, it can be easily reused in many VR and AR applications. Over the last decades, we have seen a colossal effort of many experts in different scientific fields to build and share their own ontologies (e.g., life sciences (Good and Wilkinson 2006), climatology (Lefort et al. 2017), biomedicine (Whetzel et al. 2011)).

In the survey done by Kraus et al. (2022) on IA with abstract 3D visualisations, the authors highlighted that the use of VR in IA is more dominant than AR. This may be due to the current limits of AR display devices, especially in the case of optical see-through Head-Mounted Displays (HMDs) or handheld devices, in terms of small field of view or low computational performance. Despite these limited capabilities, in this work, we focus on HMD-based AR interfaces for several reasons. First, they uphold the advantages found in HMD-based VR systems for big data visualisation by providing the users with an extended workspace that does not need to be anchored to physical monitors (Martins et al. 2022). Moreover, compared to VR, AR interfaces facilitate a hybrid and flexible working environment on a daily basis, making possible a cohabitation between immersive data analysis and interaction with conventional tools (e.g., desktops, office stationary for taking notes) without having to remove the headset. In addition, as in many domain applications of immersive technologies,

IA systems using AR can bring together many collaborators into a shared physical workspace without the need to use avatars to represent them. This will indeed greatly support the communication between the users equipped with or without AR headsets. Therefore, our AR technology choice was driven towards this co-located immersive collaborative context. As the first step to fulfil this ultimate goal, we aim to validate whether an ontology-based AR system can enhance user performance and experience, and therefore, a user study for single users was sufficient.

This paper proposes an exploratory study using ontology and linked data in AR-based IA. With this approach, the users can make queries easily in a database thanks to existing domain knowledge models. Ontology-based approach can also help the data filtering process to reduce the amount of data displayed in the 3D space and to highlight only points of interest. We believe that when visualising and interacting with data using AR headsets, “less is more” or minimalism philosophy is the design approach to take to increase user experience. Moreover, displaying part of the data intelligently will also help save computational resources to facilitate big and complex data rendering.

Our case study uses meteorological datasets collected from different sources. These datasets include heterogeneous and multidimensional big data on temperature, heat flux, precipitation, humidity, and wind velocity, amongst others. We consider this a typical example to demonstrate the use of AR-based IA in a real-world application. Our main contribution is designing and developing a proof of concept of an AR user interface using an ontology-based approach. To bring forth the advantages of ontology and linked data in AR applications, we examined different ontologies in meteorology and climatology. We proposed our ontology based on the existing ones. Indeed, the meteorological and climatological ontologies in the literature are often oversized or complex in terms of concepts and dependencies on other ontologies, which reduces the query performance in AR-based systems. Moreover, they also lack certain rules and concepts to allow the user to formulate queries accurately for some specific parts of our complex datasets. Finally, we evaluated the potential of our AR-based IA system in conducting an experiment that aims to demonstrate the relevance of our semantic approach compared to a conventional non-ontological one.

The paper is organised as follows. Section 2 presents relevant existing research. Section 3 introduces our semantic IA framework. Section 4 details the evaluation of the ontology application in IA. Finally, we conclude our use case study and discuss open problems and future work in Section 5.

## 2 Related Work

This section explores previous research on AR in Meteorology and Climatology, as well as some existing ontologies in these fields and their combination with AR technology. We will conclude this section with some discussion.

### 2.1 AR in Meteorology and Climatology

Meteorological and climatological data analysis often requires the visualisation and manipulation of large amount of data. In practice, the analysis process relies heavily on

visualisation methods using weather maps and different types of diagrams and graphs to represent the data. Most researchers in meteorology and climatology use desktop-based 3D open-source software (e.g., Met.3D (Rautenhaus et al. 2015), VAPOR (Li et al. 2019), ParaView (Ahrens et al. 2005)), and the commercial software (e.g., Iris Explorer (Walton 2003), Amira-Avizo (Thermo Fisher Scientific 2020)) are rarely employed (Rautenhaus et al. 2017). These tools can be classified into two categories according to their utility: in a research context and in an operational forecasting setting (Papathomas et al. 1988). According to Koppert et al. (1998), the research tools are mostly used to explore data from observations or simulations to find correlations between numerical variables and real meteorological phenomena. Therefore, ideally those systems must be complex but flexible enough to adapt to different exploration and analysis tasks as well as various data formats, and be configurable by different types of users (novices and experts). On the other hand, forecasting tools have to be designed with few parameters and be usable in the most efficient way possible.

Putting aside the ongoing debate on whether to use 2D or 3D for data visualisation (e.g., Dübel et al. 2014; Merwin and Wickens 1991), visualising and interacting with meteorological and/or climatological data on traditional monitors may affect user experience. Many studies have been conducted to determine the potential of AR in these fields. In the research context, AR interfaces have often been used in weather simulation. For instance, Trembilski (2003) is one of the earliest studies on augmented video for cloud and sky simulation. Also, an AR simulator was proposed to visualise precipitation data (rain, snow, and hail) (Heinrich et al. 2008). Recently, Ritterbusch et al. 2013, through the simulation of urban wind flow, demonstrated the advantages of mobile AR in facilitating access to simulation results. Besides the simulation, for scientific data analysis, there are different IA tools designed to plot different graphs of meteorological and climatological data. Sicat et al. 2018 show that their toolkit can be used to visualise weather data and how it can be helpful for collaborative tasks. Their system was designed for hurricane data, but it was limited to only a few thousands of data points. IATK (Cordeil et al. 2019) asserts to be able to visualise to a much larger number of data points. For the weather forecasting, few works were done (e.g., Leu et al. 2014; Chen et al. 2012), and most of them were based on mobile AR because of their promoted accessibility to the large public.

Apart from scientific and weather forecast context, the AR interfaces have been used for other applications. For instance, regarding environmental monitoring, some works have combined the Internet of Things with AR interfaces (Pokric et al. 2015; Veas et al. 2013). They are used to overlay information (e.g., air temperature, oxygen rate in the air), informing the user about the surrounding environment in real-time. And for training about meteorological concepts through AR-based serious games is another application. Murrell et al. 2020 show that AR can increase students' engagement to learn the basics of meteorology in large lecture class. Meister et al. 2021 confirm that AR technology can improve the training of aviation students on weather conditions.

In summary, the existing IA tools proposed in the literature regarding scientific data visualization present some limits when they are used for meteorological and/or climatological data analysis on AR interfaces. Indeed, they often do not take into

account the reduced field of view of the AR displays, especially with regard to head-mounted displays such as Microsoft HoloLens. Given this constraint, we consider that allowing the users to query and filter the data in a flexible and meaningful way will keep the system from overwhelming them with too much information.

## 2.2 Ontology and Linked Data in Immersive Environment

In computer science, an ontology is defined as “a formal, explicit specification of a shared conceptualization” (Studer et al. 1998). The principal components of an ontology are classes (or concepts), properties (or attributes), instances (or class members), and relations. Domain-specific ontologies are used to semantically describe and model existing concepts and knowledge. For instance, they help to tackle the explosion of information (Mena et al. 1998; Kalfoglou and Schorlemmer 2003; Mate et al. 2015), to facilitate the interconnection of data sources (linked data) (Castano et al. 2001; Kushida et al. 2019), to solve the problems of data integration (Buccella et al. 2003; Ekaputra et al. 2017) and interoperability (Gandon et al. 2012), to target the issue of spatial-temporal dimensions and heterogeneous environmental data visualisation (Tran et al. 2016).

In VR, ontology is often used in many types of applications. For example, Pellens et al. (2005) used an ontology to define how objects behave in the virtual environment, while Aubry et al. (2007) proposed to structure and organise the knowledge model associated with annotations using ontology. Edward et al. (2010) used the ontological approach to manage a virtual environment for risk prevention. Additionally, Moreno et al. (2011) employed this technique to enhance simulation realism and integrate different data sources. Another example is Trellet et al. (2016)’s work which unified the interaction between 3D structures and 2D data analysis of molecules with ontology. Youcef et al. (2021) utilised ontology to normalise terminology in cataract surgery training in VR. Lastly, Chokwitthaya et al. (2023) used ontology to standardise VR experiments on human-building interactions.

In AR applications, ontology and linked data can be used to increase dynamic context-awareness of the physical world. For instance, they have been used to display the contextual information about cultural heritage sites (Aart et al. 2010; Kim et al. 2017; Aliprantis et al. 2018), to specify geographic locations (Aart et al. 2010; Hervás et al. 2013), to support maintenance or training on complex systems (Toro et al. 2007; Jo et al. 2014; Akbarinasaji and Homayounvala 2017; Gattullo et al. 2020). Such semantic-based approach for context-awareness in AR is also useful for healthcare and well-being: to support daily patients’ needs (Hervas et al. 2011, 2013), or for elderly dependent users (Hervás et al. 2011).

Besides context awareness, semantic-based approach in AR has been used for scientific data visualisation. An example is DatAR (Tanhaei et al. 2019), an IA environment for the visualisation of neuroscientific concepts. However, regarding meteorological and climatologist scientific data, we did not find any AR system based on ontology and linked data. Moreover, for other application fields, no user experiment has been conducted to study the impact of such approach in terms of usability, performance, and effort for the users to solve data analysis tasks.

## 2.3 Ontology and Linked Data for Meteorology and Climatology

To link and share meteorology and climatology data easily without restriction, different ontologies have been created.

SWEET (Semantic Web for Earth and Environmental Terminology) is one of the early projects on weather conceptualisation into ontology and linked data (R. Raskin and M. Pan 2003; R. G. Raskin and M. J. Pan 2005). It is a set of 200 ontologies containing about 6,000 concepts developed by NASA's Jet Propulsion Laboratory (1936). Its initial version was based on DAML+OIL (McGuinness et al. 2002) and the current version (SWEET 2.3) on OWL 2. Built on top of SWEET ontology, NNEW (Next Generation Network Enabled Weather) (Braeckel 2009) was promoted in the NextGen (Next Generation Air Transport System (2008)) project. It especially introduces additional weather phenomena and concepts as well as relations to develop a 4-dimension weather data cube (4-D Wx Data Cube). Both SWEET and NNEW contain concepts describing complex meteorological phenomena to be used as core ontology. However, they are partitioned into several ontologies and there are dependencies between them. Using an ontology requires importing all of its dependencies. It can overload the database and thus affect its response time, while the response time of the database is important for smooth and real time AR interaction.

Sensor Web Enablement (SWE) (Simonis 2008) proposed by Open Geospatial Consortium (OGC) (Rees 2013) was set up to describe sensors, sensor observations, and sensor interface definitions. It is based on seven top-level concepts (i.e., Feature, Observation, ObservationCollection, Process, PropertyType, ResultData, and UnitOfMeasurement), excluding the location and time concept which are imported from other sources. Inspired by SWE, an ontology based on OWL 2 was created by W3C Semantic Sensor Network Incubator group. It is called SSN (Semantic Sensor Network) ontology (Compton et al. 2012). It uses DUL (DOLCE-UltraLite) (Prezutti and Gangemi 2016) as an upper-level ontology and adds additional concepts to describe sensors. Since SSN is the standard ontology of semantic sensor web, we used it as the main core of our own meteorological ontology.

Several ontologies emerged later which extends the SSN with new concepts describing time, location, or measurements: AEMET (Atemezing et al. 2013), SMEAR (Stocker et al. 2014) and ACORN-SAT (Lefort et al. 2017). AEMET ontology was designed to publish dataset of the Spanish Meteorological Office in the form of linked data. It consists of four modules: measurements, sensors, time, and location. This ontology, however, does not define classes for complex meteorological phenomena. On the other hand, SMEAR ontology has been designed to describe environmental phenomena dataset. It was set up as a software framework (called Wavellite) to organise and interpret sensor data for atmospheric monitoring. It is based on four ontologies (WURVOC, SSN, QB, and STO) to structure information according to four layers (measurement, observation, derivation, and situation). Finally, ACORN-SAT is the ontology proposed to publish the Australian Bureau of Meteorology (BOM) dataset (daily temperature records over the last 100 years) as linked data. It focuses on the description of temperature and rainfall data. Moreover, it does not contain classes

for complex meteorological phenomena such as hurricane, storm, or sea and wind characteristics.

To conclude, we do not use ACORN-SAT as it does not describe the meteorological phenomena which are necessary in our application. In addition, SMEAR ontology is too software depend to be reused in our context. And with regard to AEMET, we aim to use a more simplified version by not including the location and measurement unit classes. Instead, we incorporate only some basic ontologies (SSN, WGS84\_pos (Brickley 2004), time (Hobbs and F. Pan 2006), and units (Rijgersberg et al. 2013)) and add new classes to describe complex weather phenomena which are currently missing in SSN.

## 2.4 Discussion

In Section 2.1, we find that while AR provides great potential for meteorological data analytics. However, the limited field of view of some AR head-mounted display may hinder the analyse process when there is too much data to visualise all at once which happens often in this context. Therefore, we propose an approach based on ontology context modelling and reasoning. This approach will facilitate intelligent data integration and allow resampling of the dataset during the interaction.

As highlighted in Section 2.3, the existing ontologies for meteorology and climatology are often very large or complex in terms of concepts/classes and dependencies (e.g., SWEET, NNEW). Some ontologies also lack some of the concepts that are needed in our application (e.g., SSN, AEMET, SMEAR, ACORN-SAT) or are designed for very specific datasets (e.g., AEMET, ACORN-SAT). To avoid overloading of RDF store which stores the data in the form of linked data, which is an issue for real time AR interaction, we propose an ontology using SSN as a core, extend it by other specific ontologies such as units and time, and add more classes and rules for our system.

Moreover, as reported in Section 2.2, we did not find in the literature any user experiments studying the impact of computer-assistance work based on ontology in immersive analytics. Therefore, our ultimate goal is to conduct a user study to demonstrate that ontology can enhance task performance in immersive analytics, especially in terms of usability, completion time, and effort for the user to solve data analysis tasks using AR.

## 3 Semantic Immersive Analytics Framework

We present in this section our semantic IA framework which follows the ontology and linked data approach to support the AR-based immersive analytics process to analyse meteorological data. During the design and development process, we have collaborated closely with the meteorologists at the Atmospheres Space Observations Laboratory in France to study their workflows in working with and analysing meteorological data. A preliminary prototype was tested by them. They gave valuable feedback on several interaction issues they encountered when using the HMD-based AR system. Some of their remarks impulsed the design and evaluation of a more suitable selection technique for such AR-based immersive analytics systems (Ouedraogo et al. 2022). Other feedback contributed to our work in progress on the design and evaluation of a collaborative system for IA. However, before evaluating complex collaborative tasks with



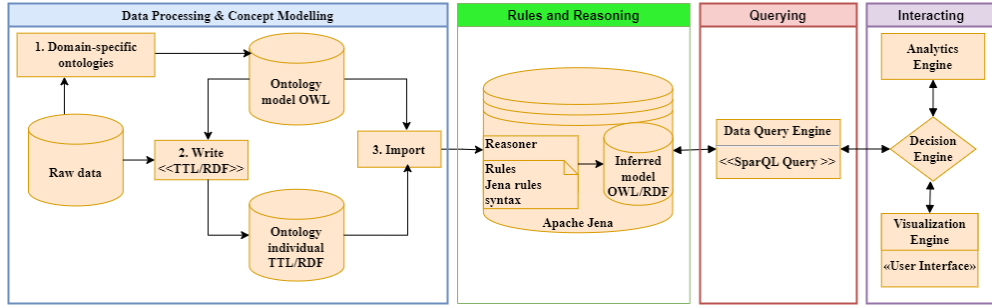


Fig. 1 Overview of our semantic immersive analytics approach.

domain experts, we aim to evaluate our AR system with a larger number of laymen to validate this ontology-based approach on basic analytics tasks with meteorological datasets. This study helps us to confirm or refute the advantages that ontology and AR can bring to the performance and especially user experience in data analytics tasks.

### 3.1 Design Overview

Our semantic IA pipeline (see Fig. 1) consists of four processes (*Data*, *Models*, *Knowledge*, and *Visualisation*) proposed by Keim et al. 2010 with some modifications. *Data* process is an essential step in our framework (cf. **Data Processing and Concept Modelling** component in Fig. 1)). It aims to transform heterogeneous data to homogeneous one. Indeed, meteorological data is mainly spatial-temporal and is collected from different sources (e.g., satellites, radar, weather balloons, etc.). It must be transformed to be used for querying and visualising. Therefore, our first concern was to set up our own ontology model in this specific domain as aforementioned. We then instantiated ontological individuals (via RDF triples) to semantically link raw data to some of the classes of our ontology.

*Visualisation* process allows the user to explore the data interactively. This process is managed by Visualisation Engine via User Interface modules of **Interacting** component in order to gain *Knowledge* from data. However, in some cases, *Visualisation* process alone is not enough to extract domain knowledge via **Querying** component, and it must be coupled with an analysis step (cf. Analytics Engine) which is characterised by the *Models* process. This process allows users to automatically extract information from data, targeting the *Knowledge* process. It is managed within **Rules and Reasoning** component, which infers the model via a reasoning engine (cf. Reasoner).

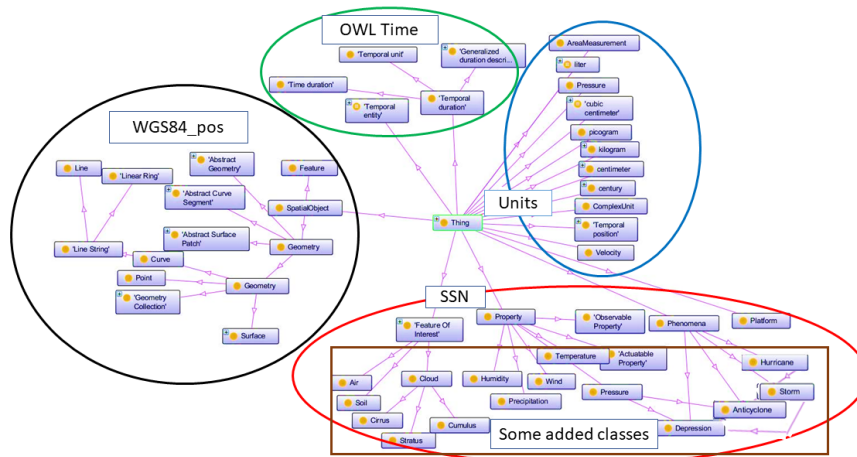
### 3.2 Data Processing and Concept Modelling

To design the domain-specific ontology, there are different approaches (e.g., Uschold and King 1995; Grüninger and Fox 1995; Fernández-López et al. 1997; Noy, McGuinness, et al. 2001) which allows us to avoid common pitfalls. We built our ontology (Fig. 2) following “Ontology development 101” approach (Noy, McGuinness, et al. 2001). This approach is divided into sequential steps as follows:

- Step 1: Identifying the domain and scope of the ontology. In this step, questions related to expertise (also called competency questions) are formulated with the meteorologists we collaborated with, and the ontology must be able to answer them. For examples, some of the formulated competency questions are:
  - **Q1**: What is the wind state according to the Beaufort scale table (Water 2005)?
  - **Q2**: Is there a depression/anticyclone?
  - **Q3**: When/Where does the cyclone phenomenon start/ends?
  - **Q4**: Where is the eye of the cyclone phenomenon?
- Step 2: Considering the reuse of existing ontologies in the context of IA, selected ontologies should be extendable and understandable, facilitating data integration and resampling. Additionally, they should have minimal dependencies to optimize query response time, crucial for real-time interaction in AR applications. Therefore, we chose to reuse in a modular structure the four following ontologies (Fig. 2): **SSN** (Compton et al. 2012), **OWL Time** (Hobbs and F. Pan 2006), **WGS84\_pos** (Brickley 2004) and **Units** (Rijgersberg et al. 2013).
- Step 3: Enumerating domain-dependent terms. This step consists in defining the terms of the ontology glossary. This glossary is extracted from competency questions (formulated in Step 1). In our case, it contains some terms such as Wind state, Light winds, Storm, Hurricane, Pressure, Cold, Dew point, Precipitation, Humidity, Wind, Sunshine, Cloud, etc.
- Step 4: Identifying concepts amongst all the terms defined in Step 3. The class of a concept either already exists in the reused ontologies and if not, this concept is added as a new class in our ontology. Following this process, we introduced 28 new classes (Fig. 2). They are then linked together to create a class hierarchy through the relationship of *subclass-of* or *is-a*.
- Step 5: Iterating over all the classes and determining the terms in the set of terminology that are properties. We identified 21 object properties and 16 data properties.
- Step 6: Specifying possible domains and ranges of values for the new properties defined in Step 5. The domain states that any resource that has a given property is an instance of one or more classes. The range states that the values of a property are instances of one or more classes (Brickley et al. 2014).
- Step 7: Defining instances of the classes and adding them into the ontology. This step transforms the data into RDF triples based on the ontology.

### 3.3 Rules and Reasoning

The inferred model (cf. **Rules and Reasoning** in Fig. 1) allows the sampling and feature extraction of data. To perform reasoning process (i.e., deducing knowledge), we need reasoners and syntactic rules. Reasoners are used to compute or derive new facts from existing knowledge. Many reasoners exist (e.g., OWLIM-lite (Bishop et al. 2012), Jena (Jena 2014), Fuxi (Ogbuji et al. 2015), EYE (De Roo 2013)) with their pros and cons (Rattanasawad et al. 2013). Amongst them, Jena is a Java-based open-source application framework for semantic web applications. We selected this framework because of its predefined reasoners, and especially its generic rule reasoner.



**Fig. 2** A representative part of our ontology model. Different modules are represented with specific colours: black, green, blue, and red representing respectively WGS84\_pos, Time, Units, and SSN (and our additional classes) ontology.

This latter provides human-readable syntax with short rules to simplify notation. It also supports user-defined rules written in Jena format.

Our ontology model was defined using basic rules between classes such as transitivity, disjunction, and equivalence. Moreover, as mentioned above, the ontologies we reused do not address specifically meteorological phenomena and we thus added concepts and properties to target them. We also introduced in the inferred model a number of rules allowing us to extract data that must be classified as an instance of specific phenomena (e.g., storm, hurricane). Some of these rules have been used to help the users perform tasks in the experiment (Section 4).

For example, rule R1 (cf. Listing 1) determining the set of data points of a depression is based on pressure property (in Hectopascal (hPa)). As a Storm *is-a* Depression, to determine if this same set of data points describes also a storm, rule R2 (cf. Listing 2) only needs to analyse the wind speed property (in m/s). Listings 1 & 2 present these rules written in Jena generic.

```

1 [isDepressionPoint:
2 (?p rdf:type local:Pressure)
3 (?p local:hasPressure ?pressure)
4 le(?pressure,1013.2)
5 (?p geo:location ?coordinate)
6 ->(?coordinate rdf:type local:Depression)]

```

**Listing 1** Depression Rule (R1).

```

1 [isThePointInStorm:
2 (?w rdf:type local:Wind)
3 (?w local:hasWindForce ?force)
4 ge(?force,17.43)le(?force, 32.63)
5 (?w geo:location ?coordinate)
6 (?coordinate rdf:type local:Depression)

```

```
7 ->(?w rdf:type local:Storm )]
```

**Listing 2** Storm Rule (R2).

### 3.4 Data Query Engine

Once the RDF database is established, it is crucial to set up a data query engine that can extract and process the data for visualisation in response to real-time interaction events from the user interface. Our system relies on the use of SPARQL query language, which is based on different query forms such as: SELECT, CONSTRUCT, ASK and DESCRIBE (Prud’hommeaux and Seaborne 2008). To support the interaction, we set up different manipulation and voice commands on the AR interface using Microsoft HoloLens 2: to trigger generic actions (e.g., show the main menu “Main menu”, to select a button “Select”), or to make queries on field-dependent information (e.g., to display data of “Wind Velocity”, “Pressure”, “Depression”, “Storm Zone”, etc.). The querying process (cf. **Querying** in Fig. 1) allows the user to filter or resample the data.

For example, via a SELECT operation automatically generated by a simple voice command, the user can request part of data which satisfies the specific rule R2 about the storm to highlight the related data points in the immersive environment (see Fig. 3).



**Fig. 3** A) Data points resulting from “Storm Zone” voice command. B) The corresponding SPARQL query to find all data points (individuals) belonging to the inference class Storm during a specific interval of time.

The user can also trigger an ASK operator to check whether an instance belongs to a specific class or satisfies some criteria. Some examples of ASK command include:

- To check if a class belongs to another class.

```

1 ASK {local: Strabus
2   rdfs: subClassOf local: Cloud
3 }

```

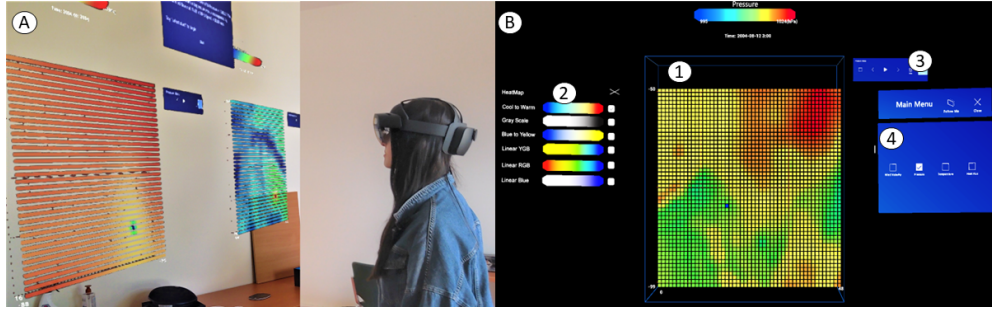
The response is true for this case.

- To check if an individual of a specific class satisfies some criteria:

```

1 ASK {
2   ?class a local:Storm;
3   geo:location ?location.
}

```



**Fig. 4** A) A user performs meteorological data exploration and analysis tasks using an Augmented Reality headset. The data is linked between graphs, which facilitates the analysis of associated variables of a phenomenon. B) Some features implemented for spatial-temporal data exploration: (1) Bounding box for data manipulation, (2) Toolbox offering different colour maps for data visualisation, (3) Toolbox for animations of spatio-temporal data, and (4) Main menu to choose the weather observation(s) to visualise. Thanks to ontology and linked data, it is possible to animate different variables in the same temporal context.

```

4   ?location geo:lat "150"^^unit:deg;
5         geo:long "-20"^^unit:deg.
6 }

```

This request checks whether the data point with latitude of 150 degrees and longitude of -20 degrees in the database is situated in a storm area.

- To perform some reasoning by automatically using SPARQL queries.

```

1 ASK {ssn: 'Feature Of Interest'
2     rdfs: subclassOf local: Cirrus
3 }

```

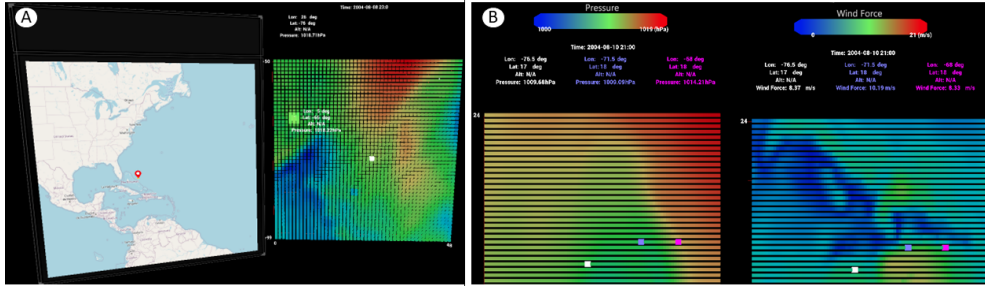
The response will be true despite the absence of an explicit direct link between the two concepts.

The data resampling (Martinez et al. 2012) based on this querying process allows the user to visualise only the data of interest. In the context of AR-based IA, it is beneficial from two main aspects. First, in terms of visualisation and interaction, the limited field of view of some AR headsets makes their use tiring for the user, which can affect user experience. The resampling helps to filter the data to show only relevant parts of it, and thus may enhance user performance and decrease their workload. Second, concerning computational power, this process will help to save the GPU calculation to facilitate big and complex data rendering.

### 3.5 Analytics Engine and Interaction

The IA environment has been designed based on the features and limitations of the AR device (Microsoft HoloLens 2) we used in this study (see Fig. 4). Our system follows a client-server architecture that separates database management and interaction components.

The AR interface allows the user to integrate data from different sources and to understand the relationship between the data thanks to the semantic links. It can be used by both novice and advanced users. We focus on AR technology for immersive



**Fig. 5** A) The user interacts with the graph and the map: when they select a data point, it is highlighted on the map. B) The user can display together several graphs (e.g., pressure, temperature, wind velocity, etc.): when a point is selected on a graph, the corresponding points are automatically selected on the others.

analytics because it provides the user with a large workspace and its potential for co-localised immersive collaboration.

We implemented different interaction techniques following the O+D design paradigm for interactive data exploration at various levels of detail (Cockburn et al. 2009; Shneiderman 2003). For instance, with Context-on-demand, the user can see all the details of a particular point by selecting it (Fig. 5). The system also supports voice commands and air-tap gestures to confirm the selection. The touch interaction was implemented, but due to a tracking issue and the large number of data points in the experiment (Section 4), it was not accurate for selection and is not considered in our study. Moreover, Microsoft HoloLens 2 headset’s existing pointing techniques (i.e., hand-based, head-based, and eye-gaze-based pointing) do not help to avoid the Eisenberg effect (Bowman et al. 2001) when selecting distant and small objects. To overcome this issue, we chose to use Expanded Data Points selection technique proposed in Ouedraogo et al. (2022). Since we also deal with temporal datasets, we implemented both automated and manual control of animation to visualise the data which changes over time.

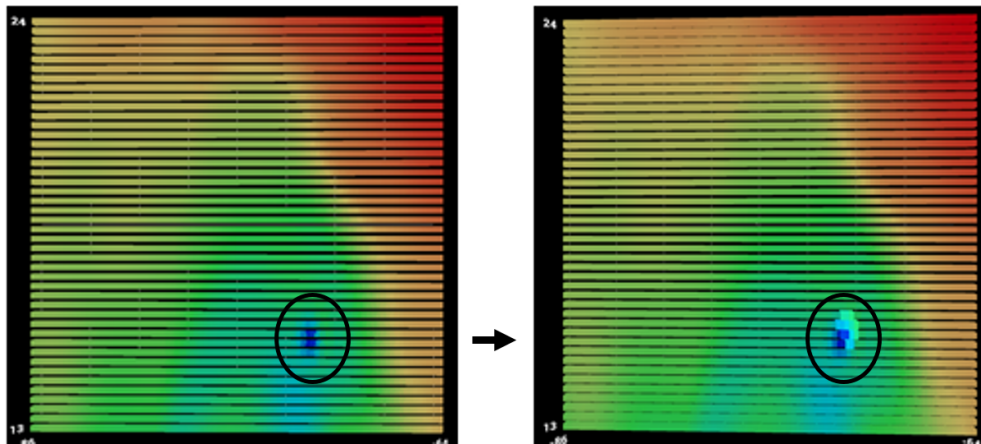
The user can make queries of different types of data (e.g., pressure, temperature, humidity, wind) and visualise it in graphs or scatterplots. Thanks to the links created between them in the ontology, when the user selects a data point in one representation, its corresponding points are also selected in others (Fig. 5.B). In addition, they can display a world map to pinpoint the source of the data based on the real spatial coordinates (Fig. 5.A). They can use two types of data representation: a pixel-based board for 2D data based on its longitude and latitude, and a voxel-based volume for 3D data with its 3D coordinates. The pixel-based board is a graph in which each cell is colour encoded. It illustrates meteorological data in conventional way by using colour maps to indicate the value of physical quantities (e.g., wind speed, pressure, humidity, etc.). Similarly, the voxel-based volume provides an overview of the multi-dimensional data in 3D space. For smooth rendering and performance management on Microsoft HoloLens 2, we used graphical shaders for data visualisations.

## 4 Use Case Study

We conducted an experiment to compare our ontological approach with the non-ontological baseline using an AR Microsoft HoloLens 2 headset.

The experiment follows a counter-balanced within-subjects design with repeated measures and two independent factors considered as follows:

- APPROACH (A) indicates whether the user uses *computer-assisted* (A1) or *non-computer-assisted* method (A2). Using A1, the user can get help from the underlying architecture of ontology and linked data (Fig. 6). For example, for task T2 (see Sec. 4.4), they can trigger a SPARQL query via voice command “Storm Zone” to automatically select all the data points belonging to a storm zone instead of manually looking for them. With A2, the data is stored in a MongoDB database under the document format. The user solves the tasks themselves based on given rules (e.g., Rule 1: a storm occurs when a depression area is accompanied by circular wind flow and wind speed between 17.43 and 32.63 m/s).



**Fig. 6** When the user focuses their cursor on the graph and says “Storm Zone”, all the data points belonging to a storm zone which satisfy the rule R2 (Listing 2) are highlighted in a more vivid colour. This region of interest is rounded by a black circle in the two figures for the readability purpose.

- TASK (T) consists of three types of tasks (see Sec. 4.4) selected in the context of meteorological data analysis. Since we conducted this experiment in the Covid pandemic context with the participants from our university who are novice in this specific domain, the tasks were simplified.

In this experiment, we used the data which includes surface pressure and wind speed from 09/08/2004 to 16/08/2004 simulating Hurricane Charley proposed by Crosby and Dietrich 2018. Nine separate subsets of the data were picked for training and evaluation tasks.

## 4.1 Hypotheses

We assume that *computer-assisted* data analysis approach provides the user an intelligent heterogeneous data integration and analysis in the IA environment, thus it would improve the analysis task performance. We formulated the following hypotheses:

- H1** It takes less time and effort for the user to solve data analysis tasks with the *computer-assisted* approach than with a *non-computer-assisted* one.
- H2** The *computer-assisted* will produce the least amount of errors and increase the user’s confidence in their answers to the tasks.

## 4.2 Participants

Sixteen participants participated in this experiment, including four females and 12 males aged between 19 and 30 years old ( $\mu = 24.25$ ,  $\sigma = 3.66$ ) from our university. 14 were computer scientists, 13 had previously used an AR headset, and seven had used 3D visualisation software (e.g., CAD, 3D modeling, 3D data visualisation). None of them had worked with meteorological data before. As meteorologists contributed to designing and evaluating the first prototype using the talk-aloud approach, we recruited non-experts in meteorology for this study to gain a more generalized understanding of the ontological approach’s performance with basic data analytics tasks. They could also provide valuable feedback for refining the system and making it applicable to a wider range of users and immersive analytics scenarios in various domain applications.

## 4.3 Apparatus

The system was developed in Unity3D and ran on a Windows computer of Intel Xeon w-2135 processor, 32 GB RAM, and RTX 4000 graphics card. Microsoft HoloLens 2 was used for rendering and interaction. The 5 GHz Wi-Fi connected the desktop to the headset. Regarding the databases, we used Apache Jena Fuseki server for ontology and linked data for A1, and MongoDB for document data for A2 on Windows 10. MongoDB (Room 2021) is a NoSQL document database that allows flexible and scalable data storage, retrieval, and manipulation, making it popular for web, mobile, VR and AR applications.

We performed a comparison between these two databases in terms of query response time according to the number of queried data points (see Fig. 7). The test was run on the same data using the same hardware for our experiment. It shows the disadvantage of the Apache Jena Fuseki server when the number of queried data points at one time increases over 1 million.

## 4.4 Experimental Tasks

There are three tasks T1 to T3 with increasing complexity (see Table 1) chosen according to the meteorological data analysis task process. Each task was solved within the two conditions (A1 and A2) on different datasets to limit the learning effect. T1 and T3 have two equivalent sub-tasks, X and Y, using two separate datasets. For example, if the T1X was used for A1 then T1Y was used for A2, and vice versa. There



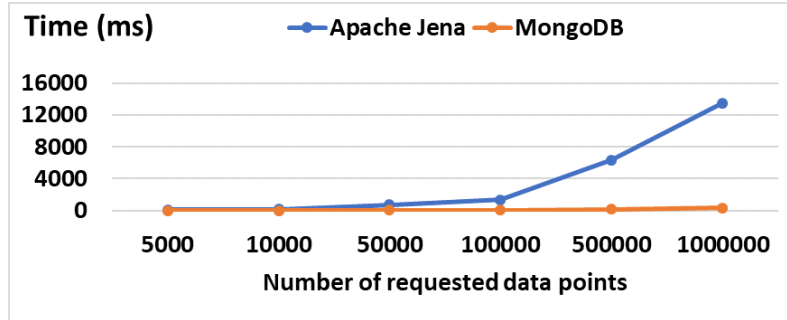


Fig. 7 Query response time according to the number of queried data points using two types of database server.

ID	Task
T1X	1. Find three <b>lowest</b> pressure points in Pressure graph 2. Validate the corresponding points with the same coordinates in Wind Velocity graph
T1Y	1. Find three <b>highest</b> pressure points in Pressure graph 2. Validate the corresponding points with the same coordinates in Wind Velocity graph
T2	Find four points in the storm area in both the Pressure graph and Wind Velocity graph
T3X	Find the points in the storm area in both Pressure and Wind Velocity graph on 12/08/2004 at 02:00 & 17:00, and on 13/08/2004 at 11:00
T3Y	Find the points in the storm area on both Pressure and Wind Velocity graph on 10/08/2004 at 21:00, 22:00 & 23:00

Table 1 Three types of tasks in the experiment.

were 2450 data points for each graph in T1 and 3872 in T2. In T3, there were 3872 data points for each graph in each timestamp.

During T1, the participants must find the three lowest/highest pressure data points and their corresponding wind velocity. With T1 in A1 condition, thanks to the linked data, when the participant selected a data point in Pressure graph, its corresponding point was automatically highlighted in Wind Velocity graph (Fig. 5.B). With T1 in A2, they had to identify manually the corresponding wind velocity.

With T2 in A1, the participant could use the voice command “Storm Zone” (not mandatory), which triggered a SPARQL query to select all the data points for the specific date satisfying the rule R2 (Fig. 6). The user had to check before validating their choices. With T2 in A2, in order to balance the average time between the two conditions A1 and A2, the user had to find only four points in the storm areas.

Finally, in T3, they performed the task similar to T2 at three different timestamps.

## 4.5 Procedure

Each session lasted about 75 minutes. At the beginning, each participant was welcomed, signed a consent form, and received an introduction to the system. Next, they filled out a pre-experimental questionnaire on demographic information. Afterward, they were equipped with the AR headset. A pre-training session was conducted to familiarise the participant with the use of the headset, the user interface, its functions and interactions.

There was a training phase before each task when the meteorological concepts and task instructions were explained on a training dataset. Next, the participant started a task in A1 and A2 conditions in a counter-balanced order on two different datasets. After each condition, they filled out two questionnaires: the NASA-TLX for cognitive load and the SUS for system usability. At the end of the current task, the participant also ranked the two conditions according to their preference and rated their confidence in the answers. The same process was repeated for all of the three tasks.

## 4.6 Data Collection

We collected data from 96 trials: 2 APPROACHES  $\times$  3 TASKS  $\times$  16 participants. For each trial, we registered the following measures.

### Quantitative data:

- *Task Completion Time (TCT)*: the time needed to complete the task in each condition. It started when the participant initiated the task and ended once it was done. This time did not include the response time of queries to the databases.
- *Number of attempts*: the number of times the participant tried to reach requested data points during the task. It was calculated based on the number of times the cursor passes over them.
- *Answers to tasks*: the number of data points correctly selected. It was used to evaluate the correctness of the answers.

### Subjective data:

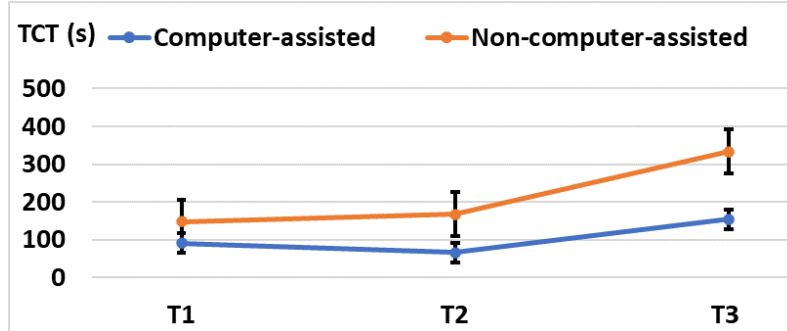
- *System Usability Scale (SUS)*: the usability of each approach (A1 and A2) estimated after the task.
- *NASA-TLX*: the cognitive load of each approach estimated after the task.
- *Overall ranking*: the ranking of the two approaches according to the preference of the participant for each task.
- *Confidence score*: the degree of confidence in the participant's answer from 1 (not at all confident) to 7 (very confident) after having solved the task.

## 4.7 Statistical Results

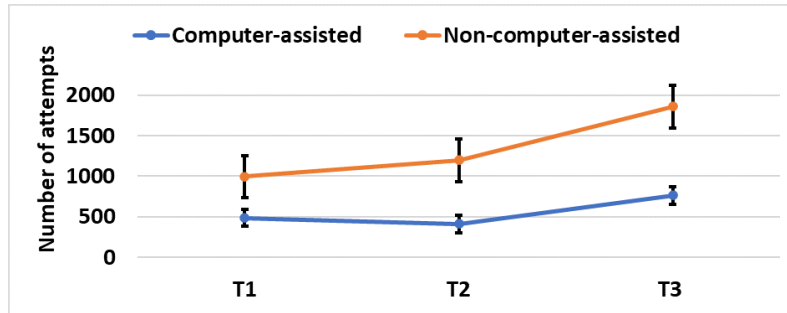
**Quantitative data:** We used normal QQ-plots and Shapiro-Wilk tests to analyse the normality of all the data from the three quantitative measurements. Since none was normally distributed, we applied a log-transformation after an asymmetry test.

Regarding the *Task Completion Time (TCT)* (see Fig. 8), a two-way repeated-measures ANOVA was used to evaluate the interaction of the two factors APPROACH

and TASK. The result revealed that there was no significant interaction between them ( $F_{2,90} = 0.80, p = 0.41$ ). The main effect test was performed and the result showed a significantly independent effect of APPROACH ( $F_{1,90} = 44, p < 0.001$ ) as well as TASK ( $F_{2,90} = 20.7, p < 0.001$ ) on *TCT*.



**Fig. 8** Means and 95% CIs of *Task Completion Time (TCT)* for the two approaches and the three tasks.



**Fig. 9** Means and 95% CIs of *Number of attempts* for both of the approaches and the three tasks.

From the *Number of attempts* (see Fig. 9), we analysed the interaction of the two factors using two-way repeated-measures ANOVA. We did not find any significant interaction effect between them ( $F_{2,90} = 0.09, p = 0.91$ ). The main effect test showed that there was a significantly independent effect of APPROACH ( $F_{2,90} = 8.60, p < 0.001$ ) and TASK ( $F_{2,90} = 11, p < 0.001$ ).

To evaluate the correctness of *Answers to tasks*, the participants' responses were transformed into numerical data. We converted correct answers into 1 while the false ones into 0. The final result showed that there were only two wrong answers.

**Subjective data:** With the answers from *System Usability Scale (SUS)* questionnaire, we used its score calculation method to compute *usability score*. The pair-sample t-test was used to compare the mean SUS scale values in *computer-assisted* ( $\mu = 81.30, \sigma = 13.14$ ) and *non-computer-assisted* ( $\mu = 71.77, \sigma = 16.60$ ). We found that there was a significant difference in the score ( $p < 0.05$ ).

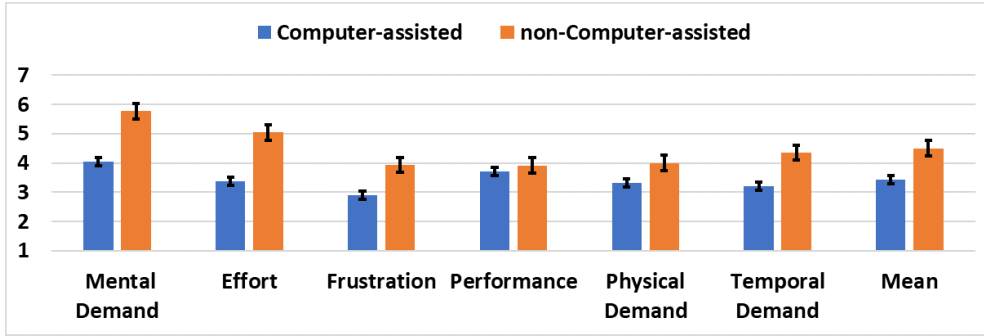


Fig. 10 NASA-TLX results are detailed in subscales for the two approaches.

Concerning *NASA-TLX* (Fig. 10), we used Wilcoxon signed-rank tests to analyse the overall workload. There was a significant difference between *computer-assisted* ( $\mu = 24.24, \sigma = 17.02$ ) and *non-computer-assisted* ( $\mu = 35.04, \sigma = 14.58$ ) workload ( $p < 0.001$ ).

The answers from *Overall ranking* showed that all of the participants preferred *computer-assisted* approach for *T1*, and 15 of them preferred the same approach for *T2* and *T3*.

We used Wilcoxon signed-rank tests for crossed comparison of *Confidence score*. There was no significant difference found between *computer-assisted* ( $\mu = 6.06, \sigma = 1.04$ ) and *non-computer-assisted* ( $\mu = 5.83, \sigma = 0.16$ ) on the score of confidence.

## 4.8 Discussion

The statistical analysis showed that *computer-assisted* approach based on ontology outperformed *non-computer-assisted* by means of *Task Completion Time (TCT)*. We also found that *computer-assisted* task required significant fewer number of attempts made by the participants to solve the tasks. These two results support **H1**.

The answers to the tasks the participants gave were mostly correct for both conditions. The confidence score was also similarly rated. Therefore, we cannot confirm **H2**. Both of these measurements can be explained by the fact that each participant was very well trained in different interaction techniques employed in the tasks as well as the minimum meteorological concepts required.

In terms of *usability score*, both of the approaches were rated positively in all the tasks even though *computer-assisted* was significantly rated higher on average than *non-computer-assisted*. The participants perceived that solving the tasks using *computer-assisted* significantly reduced the cognitive load compared to *non-computer-assisted*. Overall, they preferred *computer-assisted* based on ontological approach to *non-computer-assisted* according to the questionnaires' answers. In general, *computer-assisted* approach received overwhelmingly positive feedback from all the participants.

The high *usability score* of the semantic approach confirms that it can be used to visualise and analyse complex data for meteorology. Using the same methodology can help to get this approach go beyond the meteorology domain. Specifically, considering an application field using immersive analytics, we can first analyse the concepts and

knowledge required in the related domain to determine if some existing ontologies can be combined and/or extended to target the application. The second step is to establish domain-dependent inference rules to help users manage large datasets and, more specifically, to facilitate data queries in an immersive context. The third step is to tune these ontologies and rules according to the technical limitations of the chosen XR technologies. The final step is to experiment with the system using application scenarios and end-users to validate and enhance the inference rules and their related interactive paradigms.

## 5 Conclusion and Future Work

Recently, Immersive Analytics (IA) using Augmented Reality (AR) technology has gained its popularity. Although AR facilitates data exploration and user experience, it is still challenging to visualise and interact with heterogeneous and big data from different sources. It is due to computational limits and the lack of appropriate methods to integrate such data in the same immersive environment.

To fill this gap, we proposed an approach based on semantic-knowledge representation using ontology and linked data. We explored its benefits in the context of meteorological data analysis. We designed and developed an AR-based IA environment for novices and experts to work on such diverse data sources, which are conceptualised and linked within an ontology.

One of the contributions of this paper is the design of an ontology for meteorological data in AR-based IA. Following the “Ontology development 101” methodology (Noy, McGuinness, et al. 2001), the main features of this design process are: (i) identifying the domain and scope of the ontology, (ii) considering the reuse of existing ontologies, (iii) building the glossary of terms by enumerating domain dependent terms in meteorology with the end-users, (iv) identifying concepts among all this glossary, (v) iterating over all the classes to find the terms in the set of terminology that are properties, (vi) specifying the possible domains and ranges of values for each property previously defined, (vii) defining instances of the classes and adding them within the ontology. With this ontology set up, we designed and implemented an ontology-based AR system on Microsoft HoloLens 2 device for IA tasks on meteorological data.

The second contribution of this paper is the use case study we conducted to evaluate the interest of such ontological approach for an AR-based IA. In the experiment, the participants performed three different data analysis tasks under two conditions: *computer-assisted* based on ontology and linked data vs. *non-computer-assisted* using a NoSQL database (MongoDB). Excluding the query time response from the final task completion time, the *computer-assisted* approach allows the participants to solve tasks of exploring and manipulating the data faster than *non-computer-assisted* one, and all the participants rated *computer-assisted* as the best approach.

A common issue with any ontological approach is that it takes time and domain knowledge to build an accurate ontology. Apart from this, our work presents some limitations. First, regarding the user study, due to the Covid-19 condition, we could only recruit the participants from our university who were not working in meteorology and climatology. This led us to simplify the experimental tasks, which did not

show the full potential of our system in these domains. Its evaluation done by expert users would be our next step. Second, the query response time of the ontological approach increases exponentially when the number of queried data points explodes, which makes it unusable in real-time interactive systems when dealing with big data. To overcome this limitation, our short-term future work is to enhance the query execution time. We consider implementing within the client-server architecture of our system the graph-based indexing and query processing technique proposed by Kyu and Oo (2020). As a long-term perspective, we aim to assess the performance of such an IA system using AR technology in a collaboration context.

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### Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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