

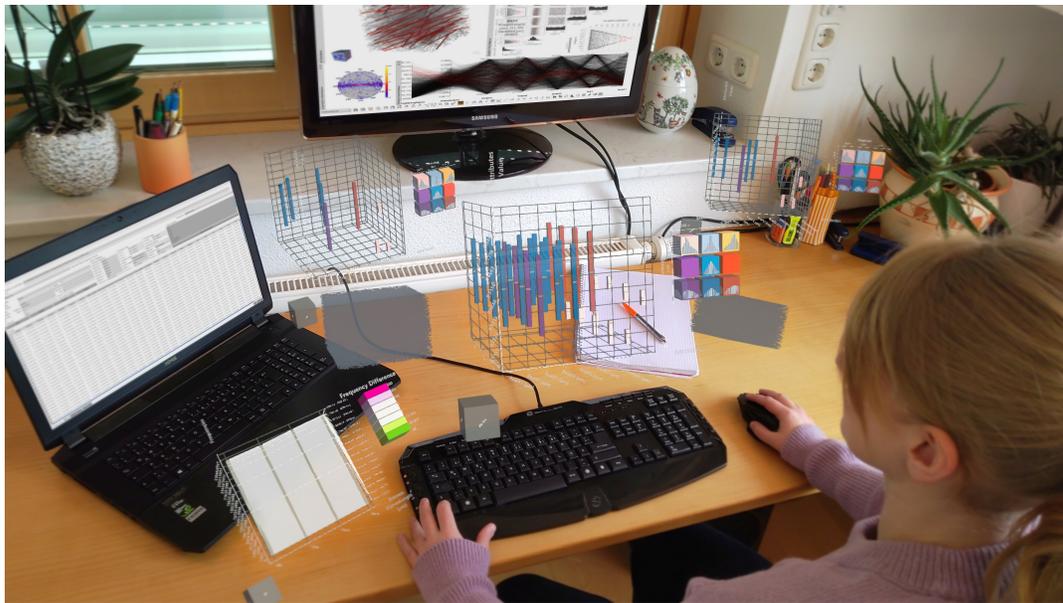
# MDD-Glyphs: Immersive Insights Through Multidimensional Distribution Glyphs

A. Gall<sup>1,2</sup>  and A. Heim<sup>1,3</sup>  and E. Gröller<sup>1</sup>  and C. Heinzl<sup>2,3</sup> 

<sup>1</sup> TU Wien, Faculty of Informatics

<sup>2</sup> University of Passau, Faculty of Computer Science and Mathematics

<sup>3</sup> Fraunhofer Institute for Integrated Circuits IIS, Division Development Center X-ray Technology



**Figure 1:** The image presents a complex multi-dimensional materials analysis scenario enabled by our AR framework. Users seamlessly blend traditional screen-based work with immersive AR exploration to explore virtual representations of spatial and abstract data.

## Abstract

Analyzing complex and large data as generated in non-destructive testing (NDT) is a time-consuming and mentally demanding challenge. Such data is heterogeneous and integrates primary and secondary derived data from materials or material systems for spatial, spatio-temporal as well as high-dimensional data analysis. Currently, materials experts mainly rely on conventional desktop systems using standard 2D visualization techniques for this purpose.

Our framework is a novel immersive visual analytics system, which supports the exploration of complex spatial structures and derived multidimensional abstract data in an augmented reality setting. It includes three novel visualization techniques: MDD-Glyphs, TimeScatter, and ChronoBins, each facilitating the interactive exploration and comparison of multidimensional distributions from multiple datasets and time steps. A qualitative evaluation conducted with materials experts and novices in a real-world case study demonstrated the benefits of the proposed visualization techniques. This evaluation also revealed that combining spatial and abstract data in an immersive environment improved their analytical capabilities and facilitated to better and faster identify patterns, anomalies, as well as changes over time.

## CCS Concepts

• **Human-centered computing** → **Visualization**; Visualization systems and tools; Interaction design; Visualization design and evaluation methods; • **Computing methodologies** → **Mixed / augmented reality**;

## 1. Introduction

In recent years, materials science experienced an immense increase in the amount and complexity of information to be analyzed and understood. Especially, non-destructive testing (NDT) contributes previously unthinkable amounts and complexities of data on materials and respective components [IM19, HKL\*19, HS17]. NDT inspections involve techniques such as X-ray computed tomography (XCT), which enables the detection of features of interest as well as defects through an accurate characterization of the internal microstructure. In this process, primary data is generated in the form of 2D images and reconstructed volumetric datasets. Such primary data can be used to derive secondary, high-dimensional data quantifying features of interest. NDT is particularly helpful for the inspection of complex materials. Composite materials, which are heterogeneous material systems consisting of matrix and reinforcement components, are experiencing a rapid growth in industry. In particular, fiber-reinforced polymer composites (FRP) are well-suited for safety-critical application areas such as automotive, aeronautics, and medicine [RPML19] due to their unique properties. For this material system, experts need to spatially and quantitatively analyze data of specimens, consisting of several hundreds of thousands of features (e.g., fibers, pores, etc.), regarding more than twenty different derived feature characteristics (i.e. attributes such as length, diameter, shape, etc.). This highly complex and cognitively demanding task becomes even more challenging when materials require comparisons across a period of time, as in the case of in situ experiments. Recent research indicates that the exploration of complex spatial data can be improved using immersive analysis techniques compared to conventional desktop monitors using standard 2D visualization techniques [DMI\*18, BCBM18, KKF\*21, KFS\*22, EBC\*21]. In particular, augmented reality (AR), a key technology of Industry 4.0, offers promising opportunities and thus experienced a strong growth in industrial use [ME20, EAB\*20]. While ARs current industrial applications are primarily in assembly and maintenance tasks, the potential for AR in areas such as material characterization and quality control, offers enormous potential for analysis in NDT [ZLL\*18, HASYF22]. Our goal is to enable experts to explore their inherently spatial material properties in a more efficient and intuitive way by enabling depth perception, efficient 3D navigation, and in-depth analysis of time-varying in situ tests. For this purpose, we have developed a generalisable framework for multidimensional augmented reality visualisations, designed to support complex spatial representations and high-dimensional abstract data visualisation.

Advancing the state of the art in terms of immersive analytics of complex and heterogeneous materials science data, our work can be summarised in the following core contributions:

- A novel Augmented Reality (AR) framework, which is focused on the analysis of multi-dimensional abstract and spatial data and applied to a real world problem from the domain of materials science.
- Three novel immersive visualization techniques, developed in close collaboration with material experts, for the interactive analysis and comparison of multiple distributions of abstract data.
  - The MDD-Glyphs visualization provides a visual summary of the statistical characteristics of attributes of interest.
  - The TimeScatter visualization offers an overview of changes in these distributions over time.
  - The ChronoBins provide a comparison of the severity of changes between datasets.
- A qualitative evaluation based on a real-world case study with material specialists and novices. The preliminary evaluation serves as basis for assessing the viability of our proposed AR framework and the developed visualization techniques.

## 2. Related Work

Conventional visual analyses in materials science mainly involve 2D desktop monitors with a mouse and keyboard as input devices. These tools are used to analyze and compare high-dimensional data that can change over time, based on both primary (i.e. volumes), and secondary data (i.e. abstract information) - a cognitively demanding task. Currently, there are only a few solutions that support material experts with immersive analytics (IA) methods and enable them to use spatial immersion and embodied navigation, leveraging their own spatial cognition skills. In their recent systematic review of immersive analytics systems, Saffo et al. [SBC\*23] identified only three applications between 2013 and 2022 that had the data types "volumetric data" and "tabular data". Systems dealing with multi-dimensional spatial data, such as CT scans, and abstract data are thus considered as limited. We therefore present studies from systems dealing with either spatial or abstract data. These cases are necessary to help identify solutions for our real-world problem, and highlight the gaps still present in the literature, particularly in AR, which we want to address.

### 2.1. Visual Analytics

Materials experts usually rely on traditional desktop-based visual analysis techniques, such as 2D charts and tabular overviews, to accurately evaluate and characterize multidimensional material data. Open source tools such as Paraview [Kit24], Quantifma [SSS\*19] and open\_iA [FWS\*19] offer visual analysis on 2D monitors to experts. Proprietary software applications such as VGStudio MAX from Volume Graphics [Vol24] or Avizo from Thermo Fisher Scientific [The24] are also commonly used to analyze the properties of volumetric data of complex material systems, such as fiber reinforced composites. Although all of these systems are used by professionals today, they all share the disadvantage that these tools are primarily designed for spatial and quantitative analyses, which is why they typically focus on 2D sectional views, 3D renderings of the volume and overviews on simple statistics. Furthermore, they all do not facilitate the analysis of inherently spatial features in the domain they are living in. When localising defects in the volume or tracking curved fibres, depth perception is lacking and navigation within or around 3D objects is difficult. In addition, these systems can only be analysed at a fixed workstation, which requires multiple monitors to allow efficient comparison of time-varying data sets.

## 2.2. Immersive Analytics

Immersive Analytics offers promising opportunities in various application areas, which are currently being explored by researchers [FP19,EBC\*21,SBC\*23,FAP\*22]. Particularly relevant to the presented materials science use case is the increase in productivity, accuracy and autonomy in the quality sector [EAB\*20,HASYF22] made possible by the key technology AR.

As lot of research is currently focused on using VR for abstract data visualization, we want to highlight some studies that overlap with parts of our challenges. The IATK framework from Cordeil et al. [CCB\*19] enables users to visualize and interact with large multivariate abstract data in a virtual environment. The DXR framework by Sicat et al. [SLC\*19] enables rapid prototyping of immersive visualizations in VR (and AR) through a declarative visualization grammar and reusable templates. DataHop by Hayatpur et al. [HXW20] allows the user to spatially layout their data analysis workflow, based on different charts, and traverse their data modification spatially. IATK, DXR, as well as DataHop revealed the positive impact of immersive data exploration but do not support the analysis of inherent spatial data.

Several studies have analyzed abstract data in AR systems. Sardana et al. [SKGM21] compared spatio-temporal data visualization between AR HMDs in immersive environments and conventional 2D displays. Hubenschmid et al. [HZBR21] demonstrated STREAM, a system that enables multimodal fluid interaction between 2D and 3D visualizations through AR HMDs and room-tracked tablets and a large screen. The proposed system of Satriadi et al. [SCT\*22] explores linking physical referents with multivariate charts for data visualization. Our task of material analysis requires the representation of spatial information in combination with its abstract data, as well as the ability to display the CT volume, in order to enable precise characterization of materials. Furthermore, Satkowski et al [SD21] investigated the effects of the real environment on the perception of 2D visualizations and concluded that the background has only a minor influence on the measured performance. VoxAR by Boorboor et al. [BCK\*23] aims to improve the volume rendering visualization of transparent HMDs by adjusting the position and coloring based on the real-world background. Although the last three studies do not provide complete systems for analyzing real-world tasks, they do demonstrate the opportunities that an AR system would provide.

In the field of VR with head-mounted displays (HMD), there are only a few approaches that focus on the visualization of data with an inherent spatial structure. Hurter et al. [HRD\*19] presented FiberClay, an immersive platform for visualizing and comparing 3D aircraft trajectories and human brain fibre traces from diffusion tensor imaging. They found that 3D selection and smooth transitions between mappings improved pattern recognition, a challenge in traditional 2D systems. For more complex volumes such as FRPs, however, their system falls short in terms of visualizing all dimensions of the secondary data. AeroVR by Tadeja et al. [TSK20] addresses the design process for aerospace components through immersive renderings of computer aided design (CAD) models with 3D scatter plots. The disadvantage of this approach is, that it is not suitable for material characterisation tasks as it does not allow the analysis of XCT scans or time-varying data. Wang

et al. [WZYW20] is concerned with the direct manipulation of CT datasets and their transfer function using hand gestures. For our use case, the application lacks the ability to visualize and analyse additional multi-dimensional data. Gall et al. [GGH21] developed the ImNDT visualization system for multidimensional secondary data exploration of FRPs. The system provided advantages in structural pattern detection. Gall et al. [GFH21] later extended ImNDT by adding a Cross-Virtuality-Analysis (XVA) and integrated an AR view for VR users collaborating via a large touchscreen. While both tools were beneficial, they do not have the capability to render CT volumes or compare time-varying material data. Additionally, the AR mode is limited by the poor resolution of the used VR camera.

An early study using AR to visualize spatial data was presented by Schickert et al. [SKB18], who visualized NDT and CAD data on physical objects using smartphones. Ferraguti et al. [FPG\*19] demonstrated an AR HMD approach for quality assessment of polished surfaces. They project metrology data onto the specimen and improve the production performance through this approach. The medical application of Pratt et al. [PIL\*18] uses the HoloLens to superimposes 3D vascular models onto the patient, enhancing precise localisation of perforating vessels. Previous systems lack embodied interaction and advanced multi-dimensional data visualization techniques, which are essential for complex material inspection. Embodied Axes by Cordeil et al. [CBC\*20] enhances AR selections in CT scans and data visualization with tangible controllers. Its superior performance over traditional trackers stresses the need for further research in handling spatial AR datasets. Exploring high-dimensional data based on spatial information and the 3D volume simultaneously is not possible, as required in materials analysis. It is not possible to explore high-dimensional abstract data in combination with spatial information and the 3D volume, or to compare time-varying data, which is required for materials analysis.

## 3. Background & Design Principles

In this section, we aim to provide a comprehensive overview of the visualization tasks and research questions, which led us to the design considerations and finally to the structure of our immersive AR analysis system.

### 3.1. Target Group, Tasks & Requirements

Since there is currently no AR analysis framework for interpreting spatial and abstract data from materials science in a single tool, it is crucial to identify the user group and their specific tasks, as well as determine the most effective design for supporting their work. To more precisely classify the design of the immersive analysis system, we apply the *Where-What-Who-Why-How* framework as presented by Marriott et al. [MCH\*18].

**Where:** Our system should be designed in such a way that it supports experts in their work processes both at a conventional desktop and outside their office. Addressing this requirement, see-through AR HMDs, such as HoloLens 2 are currently the most promising solution. Such HMDs facilitate maintaining visibility of local surroundings and work environments without delay. They also supports hands-free control, enabling interaction with physical objects

present in the surrounding. Inside-out tracking of these AR devices additionally allows for unobstructed collaboration with co-workers. Finally, it is possible to use complementary interfaces of desktop applications.

**What:** Multidimensional distributions may change over time and include a spatial reference, which defines the "what" in our system. The framework aims to ensure generalisability across data from different domains - focusing in this study on materials science. The primary spatial data is generated from 3D/4D XCT scans of material systems, which can have several gigabytes in size. The high-dimensional secondary data is based on the individual feature characteristics derived from primary data and additional spatio-temporal information. The information, which is extracted via the fiber characterization pipeline of Salaberger et al. [SKK\*11], is stored in the form of tabular \*.csv files and can consist of several hundred thousand features (i.e., fibers, pores,...), with more than twenty different derived attributes. Based on these values, additional statistical data is computed and utilized in the examination of the material data.

**Who:** Our target user group consists of individual users who analyze large amounts of abstract data with spatial reference. This study primarily focuses on NDT data, making experts and novices in the field of materials science our target users.

**Why:** Our goal is to offer a compact overview of a huge amount of time-varying multidimensional distributions to enable users an immersive standalone analysis of their data. With a focus on the domain of materials science we identified the high-level user task of discovery, which involves an exploratory search for patterns and changes in the abstract data as well as in the spatial volume [BM13]. Visualization tasks, such as determining ranges, characterizing distribution, finding anomalies, identifying correlations/trends, making comparisons [LKK17], as well as filtering, and sorting [SED19] are especially critical for materials science experts. The search is driven by exploration, so target and location are unknown. Once a target or set of targets has been found, compare, or summarize tasks are possible to find new hypotheses, as well as to verify or falsify existing ones.

**How:** The framework enables users to observe primary XCT data through Direct Volume Rendering (DVR) and to interact with and explore features using abstract data visualization techniques and model-based surface representations. Using gestures, both spatial and abstract properties can be manipulated or filtered, resulting in an interactive and comprehensive data analysis experience.

Our study represents a problem-driven research, which is why we adopt the design study methodology proposed as by Sedlmair et al. [SMM12]. During the design of the *Where-What-Who-Why-How* framework [MCH\*18] through discussions with domain experts, we identified a number of domain goals and tasks.

**G1 - Immersive Workspace:** Our NDT experts want to inspect their complex and heterogeneous XCT material data in an immersive environment, taking advantage of location-independent analysis, accurate depth perception and efficient 3D navigation.

**G2 - Simultaneous analysis of primary and secondary data:** Since material characterisation requires both spatial representation, e.g. for finding anomalies, and the derived secondary high-

dimensional abstract data for detailed analysis of the attributes' distributions, an application needs to efficiently support both.

**G3 - Analysis and Comparison of in situ tests:** The investigation of changes in the distribution of material attributes over different time steps is critical for experts to gain insights into the behaviour of materials under stress from external influences (forces, temperature, ...).

**T1 - Overview and comparative characterization of distributions:** Experts require a quick method to filter a large number of attributes, i.e. distributions, across many data sets or time steps (**G3**) in order to compare them and identify their value ranges.

**T2 - Tracking and analysing temporal changes:** Trends, anomalies and correlations in the distributions must be made visible to experts in order to effectively identify the most significant changes over time (**G3**).

**T3 - Detailed inspection of attribute-specific changes:** Experts require a detailed comparative investigation of changes in the attributes' distribution between time steps and value ranges (**G3**), allowing them to identify anomalies and relate them to the spatial representation (**G2**).

### 3.2. Research Questions

Due to the limited availability of augmented reality AR systems for material characterization, the following key research questions were identified to evaluate the usability of an AR analysis for material characterization:

**Q1 - Usability and Perception:** How do domain experts and novices perceive the experience of analyzing material data in an immersive AR environment and the intuitiveness of the data exploration process, particularly in terms of interaction, navigation, and ease of use?

**Q2 - Data Interpretation:** How does the use of different visualization techniques in the AR environment influence the users' ability to explore and interpret complex, multidimensional data and its spatial representation, especially in terms of uncovering unseen patterns, understanding correlations/trends and comprehending distributions?

## 4. Immersive Framework: Design & Description

In this section, we present several design considerations that need to be taken into account when creating visualisation techniques for AR environments and specific domain expert tasks. The main challenges that influenced the design of our framework are outlined, followed by a detailed description of our novel visualisation techniques.

### 4.1. Visualization Design Considerations

Although AR devices have several advantages (see Section 3.1), designing interactions and visual metaphors poses severe challenges. One challenge related to the device affects the size of virtual representations. See-through AR devices, such as the HoloLens 2, typically feature a limited field of view (FoV), which requires that the

developed visual representations be very compact such as to be viewed as a whole. Additionally, visualization techniques should not solely rely on color or position and size, as color fidelity in AR is low and perspective distortions can occur depending on the viewing angle and distance [KWO\*20]. It is also recommended to avoid control components that can cause fatigue due to mid-air interactions [HRGMI14].

Other challenges arise from the tasks imposed by the domain and the tasks of the experts. For material characterization and defect detection tasks, material specialists may not always have sufficient information about the target and its location, as defined by Brehmer and Munzner [BM13], for conducting their search. This means, that in order to understand the structure of the material or changes over time during in situ tests, they need a holistic overview of all attributes to explore anomalies or patterns. The visualization technique must therefore be able to display a compact representation of several attributes, i.e. distributions, with different units (angles, areas, volumes). For exploratory data analysis, it is crucial to use statistical parameters as they allow for the comparison of multiple attributes without the need for dimension reduction [CDH\*19]. Additionally, visualization techniques should allow for temporal exploration of these distributions. In situ tensile testing is a vital tool for material engineers as it enables investigation into damage mechanisms. The test involves sequentially scanning a specimen under varying, incremental load levels, starting from no load until potential fracture. This leads to numerous complex data sets that are challenging to interpret without appropriate comparative visualisation techniques, but can provide experts with a comprehensive insight into the behaviour of the material over time.

Although we try to solve most of these challenges with our framework, in the case of colour fidelity we refer to existing solutions from Hincapie-Ramos et al. [HRISI14], as this complex issue is beyond the scope of this paper

#### 4.1.1. Visual Representation

With the aforementioned requirements and challenges taken into consideration, multiple visualization methods and techniques have been investigated in the design phase of our framework, assessing their applicability to the tasks and goals identified in Section 3. The complete list of methods and their respective strengths and limitations is not possible to be included in this publication and will be provided in the supplementary material. First, we looked into techniques that can display more than 3 dimensions and different units. Promising visualization techniques in this realm include Parallel Coordinates, Radar charts, Sankey diagrams, and Glyph representations. However, some techniques (e.g., tree maps) are not suitable for the necessary tasks (T1-T3), such as determining range, and cannot be utilized. Other visualization techniques, such as parallel coordinates or radar charts [WDG\*19], can rapidly become challenging to comprehend due to the abundance of data items and revealing correlations between attributes depends on the ordering of the axes (T2). Charts that can only represent enough dimensions by being used as small multiples or stacked representations come with a common drawback: The available screen real estate constrains the number of dimensions to be effectively displayed and thus a comparison using juxtapositions becomes more challenging

(T1) [LJS21]. In addition, displaying too many attributes with a high number of data points in a small chart can result in cluttered diagrams and diminish comprehensibility (T2). For instance, displaying histograms or violin plots requires a significant amount of space, which renders the comparison of multiple plots simultaneously with a small FoV challenging while increasing cognitive efforts. Selecting appropriate marks and channels is essential for efficient analysis. After evaluation of all visualization techniques, we have decided on glyphs to be the main idiom for the design space in our study. The glyphs' geometric shape resembles bars (cuboids in the spatial domain), encoding relevant statistical measures as their channels. This will reduce the learning curve for users since box-plots and histograms composed of bars are familiar graphical display tools [SS05, SED19, RBLB19, BDL\*20, HGW\*24] and commonly used by material experts (T1-T3). Using simple shapes also eliminates potential misinterpretations caused by perspective distortions. Depending on the visualization technique, statistical measures are used to encode these glyphs by color and height to facilitate a comparison of different attributes in a compact way. We combine this familiar geometric form with embodied navigation and the avoidance of menus breaking immersion (G1). Therefore, exploration occurs solely through spatial representation and our novel MDD-Glyphs visualization. Our framework aims to address a lack in current visualization systems, which often fail to generate task-specific visual representations [AMST11]: Our MDD-Glyphs visualization technique creates a natural workflow for material experts, seamlessly transitioning from one visualization to the next as the user interacts with its components and changes viewpoint. The resulting visualization techniques and the spatial representation are described in detail in the following section.

## 4.2. Visualization and Interaction Techniques

Together with material experts, we have collaborated to develop the following techniques, which offer a powerful workflow for the analysis of material data in our framework. The techniques are demonstrated through authentic images created directly with Hololens 2 in an office environment.

### 4.2.1. Spatial Visualization

In our framework, users have two options for displaying spatial information (G2). The first option is to directly display the reconstructed XCT volume, i.e. voxel data, using direct volume rendering (DVR), maximum intensity projection, or similar techniques. The second option is to generate a model-based representation of the data by constructing spatial items from the derived secondary dataset. To achieve this, fibers are modelled as cylinders using their start and end points along with their radii. Using this approach, we can efficiently represent a wide variety of real-world fiber types and create a less cluttered representation, while reducing the use of computational resources for smooth exploration of large datasets. An illustration of the different representation methods is shown in Figure 2. The user can interact, via hand gestures, with the volumes to adjust their size, position, and orientation for precise analysis (G1).



**Figure 2:** *Spatial representations: Two techniques are available for the visualisation of spatial information. The primary data is rendered using DVR and the secondary data can be displayed as model-based surface representation.*

#### 4.2.2. MDD-Glyphs Visualization

**Goal:** The main visualization technique of our framework is called Multidimensional Distribution Glyphs (MDD-Glyphs) chart. The chart is designed as a compact representation of the statistical characteristics of multiple attributes, i.e. distributions. MDD-Glyphs charts enable experts to have a comprehensive overview of all attributes in the dataset at multiple time steps, solving Task (T1) of the experts. A concise representation is necessary, as traditional histograms, box plots, and line plots take up too much space and would not be comparable in the limited FoV. For this reason, we adopt the approach of combining the benefits of various representations and metrics, as suggested by Blumenschein et al. [BDL\*20].

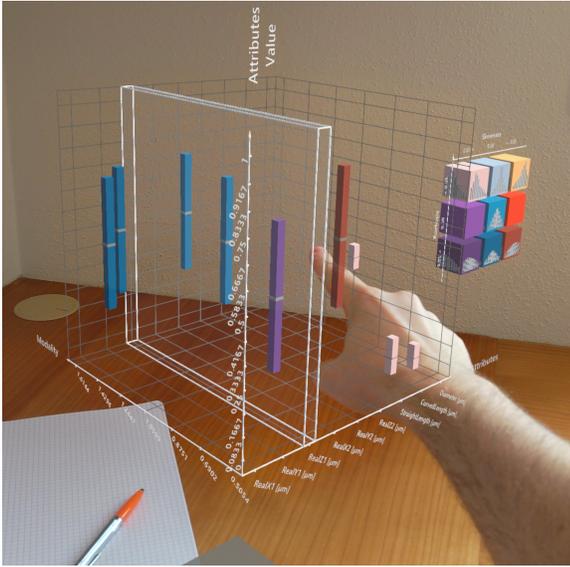
**Transition:** After loading the datasets MDD-Glyphs chart serve as an initial representation for analysis and enable the interaction with further visualization techniques. For each loaded dataset, an MDD-Glyphs can be placed in the environment and a 4D MDD-Glyphs representation is created that shows all datasets, i.e. time steps, within reach and at the user's eye level.

**Representation:** The MDD-Glyphs chart depicts a three-dimensional left-handed cartesian coordinate system with the Y-axis vertically oriented (see Figure 3). The horizontal "Attributes" axis (X-axis) displays the attributes of the secondary data. This arrangement facilitates comparison of values in a single plane, formed by the X- and Y-axis, without the challenge of perspective distortion. The vertical "Attributes Value" axis (Y-axis) displays the values of each attribute, i.e. distribution, normalized to the range [0, 1]. This mapping allows for a simultaneous comparison of aggregated attribute values, omitting individual unit information. Subsequent detailed visualization techniques however compensate for this loss in detail. Each attribute is represented by a glyph, i.e. a rectangle, with equal width and depth to avoid perspective distortion. The center of the glyph is determined using the median, similar to a box plot, and respectively marked. The height of the rectangle is scaled by the interquartile range (IQR) of the corresponding attribute distribution. By utilizing the IQR, the glyph is less susceptible to the influence of extreme values or outliers, facilitating comparison. The Z-axis serves for different purposes depending on the task at hand. When analyzing a single data set, the horizontal

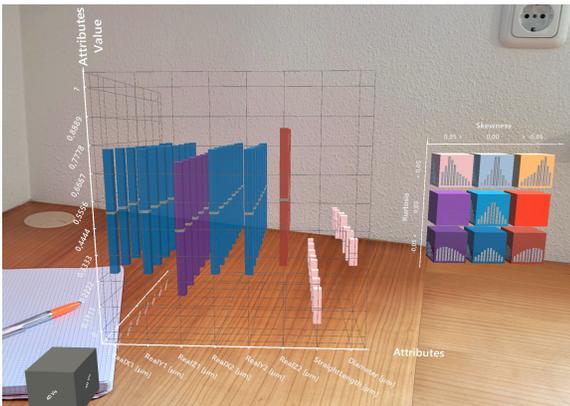
"Modality" axis (Z-axis) displays the modality (shape information) of the distribution. The modality is calculated through an iterative approach that divides the data several times into different numbers of bins of equal size and sums the absolute differences [Gre14]. The result is an approximated number of peaks in the distribution. An ascending ordering of the number of peaks on the Z-axis has the advantage that only distributions of similar shape, i.e., modality (uniform, unimodal, bimodal, and multimodal), are compared in one plane, formed by the Z- and Y-axis. If multiple sets of time-variable data are loaded, the various time steps, such as material load steps with increasing forces, are arranged along the Z-axis now labelled "Datasets" axis as can be seen in Figure 4. Finally, to include the lost symmetry, i.e. shape, information of the distributions, which would typically be displayed in a histogram or violin plot, we apply a specific color scheme to the glyphs. Our novel Colour Widget (visible on the right in Figure 4) helps to overcome some of the limitations of conventional approaches by interactively colouring the glyphs. For instance, displaying the distributions using histograms or violin plots would require a significant amount of screen space. Area plots may overlap for small changes and perform poor for comparisons [RBLB19], box plots may not show the shape effectively [RBLB19, BDL\*20], and histograms can be misinterpreted if the binning is not optimal [SMS21, HGW\*24]. Insights derived from graphical displays, such as histograms, can often be subjective and lead to deceptive shape information [Koc13]. The perception of the underlying data distribution often depends heavily on the number of bins used [SMS21]. Based on these studies, our color scheme encodes the extent to which a distribution deviates from the normal distribution [SS05].

**Interaction:** Interaction with the MDD-Glyphs chart is done through hand gestures, similar to the spatial representations. A gray cube serves as a handle for spatial manipulation. By changing the orientation of the chart and looking through a different plane formed by two axes, it is possible to observe different aspects of the distributions, such as modality or variability, or generate other views (refer to Section 4.2.3).

**Color widget:** Our color widget (see Figure 4) is designed as a bivariate color scheme [CMH18, FPS\*21] that visualizes the deviation from a normal Gaussian distribution based on kurtosis and skewness. Figure 5 depicts the color scheme of our color widget, which is arranged in a  $3 \times 3$  matrix. The bivariate color scheme is made up of three individual sequential color schemes (purple, blue and red) selected from the ColorBrewer tool by Harrower and Brewer [HB03], which we call the "categorical view". The goal was to use three distinct color schemes that are robust, colorblind safe, and easy to distinguish. Furthermore, it was important to ensure that the colors would function effectively in an AR environment with changing backgrounds. Colour schemes [LH18] such as Viridis and Magma were tested but ultimately rejected due to too low or too high luminance against the real background. Black and white were excluded as colours for the visualisation because they cannot be properly reproduced in AR. The horizontal X-axis represents the skewness value, which is defined by the three categorical colours (purple, blue and red) and indicates whether small or large values predominate. The vertical Y-axis represents the kurtosis, which divides each categorical colour into two additional sequential colours, ranging from low to high in luminosity. The



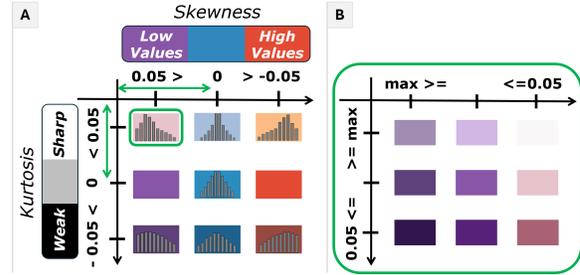
**Figure 3:** MDD-Glyphs: MDD-Glyphs chart. The Z-axis is ordered by the distribution’s modality, i.e. the number of peaks. The user points to an attribute of interest on the X-axis to make a selection, which is indicated by a semi-transparent box with a white outline.



**Figure 4:** 4D MDD-Glyphs: Comparison of eight time steps (represented on Z-axis). Our (3 × 3) color widget which visualizes the deviation from a normal Gaussian distribution is visible on the right side of the chart.

kurtosis values indicate the sharpness of the peak in the distribution. This means that a normal distribution with  $kurtosis = 0$  and  $skewness = 0$  is in the center of the matrix. The color widget can be read as follows: lower value ranges are on the right side and higher value ranges are positioned on the left, with higher frequency at the top and lower frequency further down.

**Interaction with the color widget:** Interaction with the color Widget is possible by touching one of the cells in the (3 × 3) matrix. The user can further classify the deviation from the normal distribution by the selected interval, defined by the range of skewness and kurtosis values, in the "categorical view".



**Figure 5:** (A) Categorical View: Our A widget features a bivariate colour scheme in a (3 × 3) matrix that shows the deviation from a normal distribution using kurtosis and skewness. (B) Detailed View: Each matrix cell with its interval has a corresponding sub-colour space that displays a sequential colour scheme, enabling more detailed exploration.

ness and kurtosis values, in the "categorical view". The selected range is then divided into the (3 × 3) matrix, allowing the user to 'zoom in' on the desired range of values, creating a new sub-colour space called "detailed view". The colour scheme for the "detailed view" consists of nine sequential colours based on the categorical colour of the selected cell (purple, blue and red) and is applied to the (3 × 3) matrix areas shown in A on the right. This allows for a more precise categorisation of the glyphs and subsequently the shape of the attributes' distribution. Any subsequent selection during the "detailed view" of any cell in the matrix will restore the original "categorical view" colour scheme in the glyphs and color widget, resetting to values of a normal distribution in the center of the matrix.

#### 4.2.3. TimeScatter Visualization

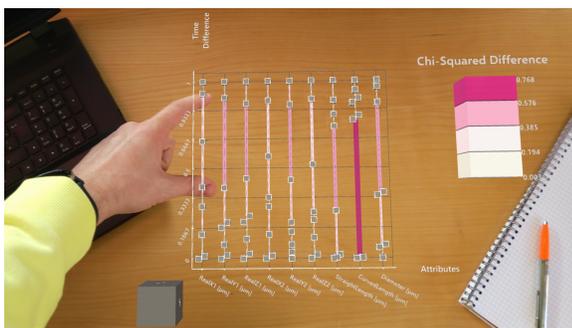
**Goal:** TimeScatter enables experts to efficiently track attribute changes across multiple time steps. The goal of the chart is to provide a clear and efficient overview of relevant information for complex time-oriented data, allowing for quick identification of the most prominent temporal changes and their magnitude. The TimeScatter chart reflects the domain goal (G3) and addresses the requirements defined by the experts in the task (T2). By simply transitioning between MDD-Glyphs and TimeScatter, users can intuitively compare the most significant changes between time steps (i.e. datasets) without requiring a new chart.

**Transition:** The TimeScatter visualization as shown in Figure 6 is triggered when interacting with the MDD-Glyphs chart. To do this, the user needs to view at the chart from the top, for example, by placing it on the floor, or turning it 90 degrees by hand.

**Representation:** This transforms the MDD-Glyphs into a 2D chart where the glyphs are transformed into cubes. The X-axis of the new coordinate system remains the same and displays the individual attributes of the data set. The Y-axis now shows the similarity of the distributions to each other two consecutive points in time, using the Chi-square test [Cha08] as the metric for calculation. The Chi-square metric is applied for this purpose due to its accuracy in comparing similar multimodal histograms without the computational intensity or complexity of alternatives like Earth

Mover's Distance [NPJ09, BDD19]. The metric is calculated for each consecutive time step of an attribute and then normalized to the interval  $[0, 1]$ . To improve feature recognition, we encode the differences between two steps in time redundantly [HGW\*24]. The small cubes represent individual time steps, with the first step at the bottom of the view and the last on top. Distributions (i.e. cubes), which are more similar to each other, are placed closer together, until they are aligned horizontally. Additionally, dissimilarity is represented by a line connecting two (distant) cubes: The thicker and more reddish the line becomes, the more dissimilar the distributions are. The sequential color scheme used for this purpose was also determined using the ColorBrewer tool [HB03].

**Interaction:** Spatial manipulation of the chart is possible with a handle in the form of a larger gray cube in the bottom left.



**Figure 6:** TimeScatter: Looking on the top of the MDD-Glyphs chart, it is transformed into the TimeScatter visualisation. The TimeScatter visualisation shows changes in attribute distributions over time. Each of the small cubes represents a point in time. The thickness and color of the line between the cubes encodes the extent of change.

#### 4.2.4. ChronoBins Visualization

**Goal:** The ChronoBins visualisation allows experts to analyse the temporal changes of an attribute, i.e. a distribution, in detail. This is achieved by calculating a histogram for each time step and stacking the bins vertically. By connecting bins of adjacent time steps with a coloured area, trends of individual value ranges can be precisely compared and analysed. The ChronoBins chart addresses domain goal (G3) and provides experts with the ability to inspect attribute-specific changes in detail, as required by task (T3).

**Transition:** By placing a hand near the MDD-Glyphs, the user can select an attribute and all its available time steps, indicated by a semi-transparent selection box with a white outline (visible in Figure 3). Dragging the box and its horizontal X-axis entry out of the chart creates the new visualization technique ChronoBins.

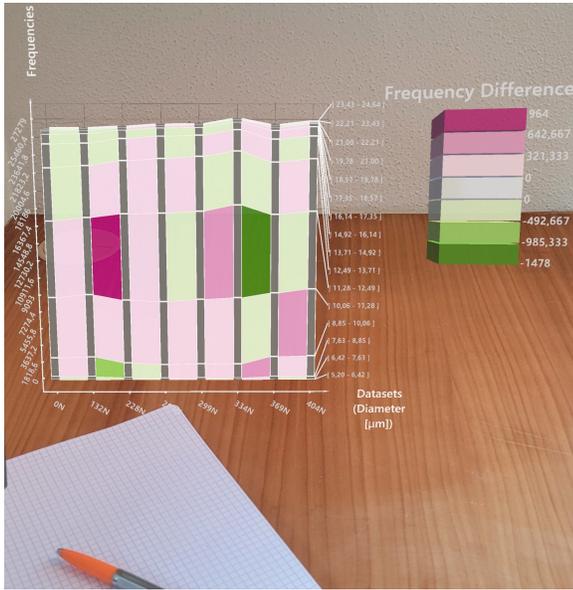
**Representation:** The ChronoBins technique is a 2D chart in which grey rectangular glyphs, i.e. bins, of different lengths are displayed stacked on top of each other. The individual stacked bars are connected by coloured areas (see Figure 7). The time steps for the selected attribute are displayed on the horizontal X-axis. The vertical Y-axis displays the total number of data points in the distribution, i.e. the frequency. According to the recommendations

in [HGW\*24] the number of bins required for each distribution is determined using Sturge's rule. A histogram is computed for each distribution using the highest required number of bins across all distributions. The grey bars in the ChronoBins chart represent the bins of the histogram of the respective time step and are stacked vertically from bottom to top from the first to the last bin. The height of the bars is scaled according to the number of data points in that bin. In conclusion, each time step on the X-axis is represented by vertically stacked bars, i.e. bins, that accumulate until reaching the maximum number of data points. The value range associated with bins of the same index is identical, due to the same order and the same number of bins. The value range, in the unit of the attribute, is displayed to the right of the final time step at the approximate height of the corresponding bin. This arrangement enables users the comparison of bins from adjacent time steps without occlusion as in traditional superimposed histograms [BKS22]. To enhance the perception of the trend of changing data points, visual metaphors familiar from Sankey plots are added to the visualization. Bins from adjacent time steps are connected by an area that indicates the increase/decrease of data points in the value range defined by the bins through its shape. To make significant changes easily visible, the areas are highlighted with different colors. A blind-safe, diverging color scheme was employed and defined using ColorBrewer [HB03]. To prevent any misinterpretations with the colours in the color widget for the MDD-Glyphs chart, we have chosen a different set of colours. An increase of data points is indicated in pink, whereas a decrease is indicated in green. Gray indicates no changes over time.

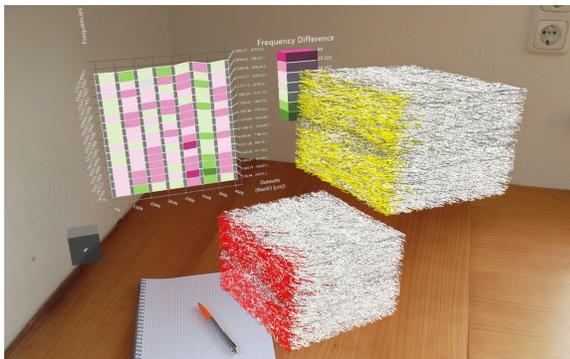
**Interaction:** The chart can be moved, rotated and resized in space using the large gray cubic handle in the bottom left. The ChronoBins visualization can be pushed back into the MDD-Glyphs chart (cf. pushing a book back onto the shelf), which will remove it. It is also possible to create multiple ChronoBins charts for different attributes at the same time. This allows comparisons to be made between different attributes over time, providing the opportunity to discover correlations in trends. Interaction with the ChronoBins' areas provides the user with additional information by combining abstract data with spatial representation. Users can click on the areas between bins of two time steps and the corresponding objects are highlighted in the respective model-based surface representations. In our materials science scenario, all fibers in the value range of the selected bin are highlighted in the color in the two different spatial representations of the time steps (see Figure 8). The first time step is marked in red and the subsequent time step is marked in yellow. This allows changes or correlations that were made visible by visualizing the abstract data to be represented directly in the spatial volume.

## 5. User Study

The overall goal of our framework is to facilitate the joint exploration of complex spatial structures and multidimensional abstract data derived thereof in an AR environment. As the presented approach is one of the few to combining these two data types in an immersive environment, especially to analyse material data, evaluation is challenging [EBC\*21]. The goal of our user study is thus to evaluate the effectiveness of our novel immersive visualization



**Figure 7:** *ChronoBins: The ChronoBins representation visualises the increase and decrease of data points of a selected attribute as stacked histogram bins. The shape and colour of the areas between bins, indicate the number of gained or lost data points, i.e. fibres, between neighbouring time steps.*



**Figure 8:** *After touching a area in the ChronoBins representation, the data points, i.e. the fibres, of the selected value range are highlighted in the spatial representations of the time steps. In the first time step the fibres are marked in red and in the next time step the fibres are marked in yellow.*

techniques on a real-world problem in the field of materials science. Therefore, our user study is guided by the research questions outlined in Section 3.2. The evaluation will assess the intuitiveness of immersive data exploration regarding interaction, navigation as well as ease of use. Furthermore, it will investigate the impact of different visualization techniques on users' ability and workload to interpret complex, multidimensional data regarding patterns, correlations, and trends in an AR environment.

## 5.1. Participants & Apparatus

We recruited ten participants (four female and six male) aged between 24 and 40 years. All invited participants have a background in materials science and use various systems to analyze and compare XCT scans. Seven of them would describe themselves as experts in material characterization. All study participants hold a university degree as their highest level of education. Seven participants reported no prior experience with AR. Two participants had moderate experience, while only one person felt somewhat experienced. The vision capabilities of all participants was confirmed to be normal or corrected to normal, ensuring that the results generated are not biased. The experiment was conducted in a typical office environment where participants could use the application either seated or standing, and they had a free movement area of  $2 \times 2$  meters.

Our system can be run either in standalone mode on the Microsoft HoloLens 2 or via remote rendering using a workstation. To allow real-time observation of participants' interactions with the system during the study, while ensuring a seamless analysis experience with minimal delay for them, we chose to use the remote rendering mode. A Windows 11 notebook with an Intel i9 9800H processor and an NVIDIA GeForce RTX 2080 Max-Q graphics card was used for this purpose. Our tool was developed using the Unity [Uni24] development platform (2021.3.14) and the MRTK (2.8.3.0) SDK [Mic24]. The source code for our framework is publicly available and can be downloaded from GitHub [Gal24].

## 5.2. Datasets

The study utilized a short glass fiber reinforced polypropylene material as the data set. Interrupted in situ tensile tests were conducted on the injection-molded material, and the material was scanned over several loading steps during these tests (more details in [MSJ\*22]). The resulting data consists of primary dataset acquired at eight (temporal) points of a loading experiment (i.e., applying a load of 0N, 132N, 228N, 263N, 299N, 334N, 369N, and 404N), and correspondingly, eight sets of secondary derived data. The secondary derived data contains between 26367 and 27279 fully characterized fibers. Each fiber is associated with up to 25 distinct attributes, of which the nine most interesting were selected for the study. As all participants have experience in analyzing fiber datasets, they are asked to perform a standard exploration (exploratory data analysis task) using our novel AR workflow in our framework.

## 5.3. Procedure

The study was conducted in accordance with all the ethical and sanitary guidelines required at the time, and the same procedure was followed for each participant. Participants completed a demographic questionnaire and were given an introduction to the features and controls of our framework using a dataset that was not part of the study. The introduction presented the exploration of a dataset using the visualization techniques we developed, including MDD-Glyphs charts, TimeScatter and ChronoBins visualization. The introduction lasted 15 minutes, during which participants were able to watch the live demonstration of the framework's features and controls on a monitor. The participants then put on the AR HMD

and we loaded the data set with eight load steps as described in the previous section. Three generic tasks were defined for the study to encourage users to test each visualization technique. Task 0 was to explore differences between the attributes in the MDD-Glyphs. In Task 1, the aim was to identify the strongest temporal change in the TimeScatter, and in Task 2, the ChronoBins visualization was used to analyse the changes in value ranges between time steps and to investigate them in the spatial visualization. Throughout the study, participants were asked to use a think-aloud protocol, which allowed to gain qualitative insights into the analysis process and potential usability issues. After each task, the participants were asked to take off the AR headset during a short break and to fill two questionnaires about the visualization techniques employed. We used the official NASA Task Load Index (NASA-TLX) [HS88] to measure the workload and the System Usability Scale (SUS) [Bro96] to measure the user experience. Participants spent approximately 30 minutes in the AR environment. This phase was followed by a semi-structured interview where the participants were asked regarding their thoughts and comments on our framework implementation. Finally, the study concluded with a short questionnaire in which participants were asked to rate their AR experience and any health problems they might have encountered on a 5-point Likert scale. In total, each study took ca. 60 minutes per participant and we collected data from 60 completed trials (10 participants  $\times$  3 visualizations  $\times$  2 questionnaires). Additionally, we gathered demographic and general information for each participant. All experts completed the full set of trials successfully.

## 6. Results & Discussion

To measure the workload associated with our visualization techniques with respect to the tasks to be completed, we use the comprehensive NASA TLX metric (six questions), where lower values (0 – 100) indicate lower workloads. To facilitate comparison with other applications, we utilize the reference values outlined in the study by Herz [Her21], focusing on the most similar technology, i.e., Virtual Reality. To assess the usability of our technologies, we utilize the commonly used SUS metric (Question SQ1-SQ10), where higher scores (0 – 100) indicate better usability. In order to allow for a better analysis of the raw SUS score, we convert the score into grades as indicated by Lewis [Lew18] and Bangor et al. [BKM09].

### 6.1. Evaluation Results

Figure 9 displays the results of our study, which overall suggest that the participants had a positive experience with our immersive framework. The Nasa TLX results are shown in Figure 9 A, where the lowest workload of all categories combined (Mean) was measured for TimeScatter (23.08), followed by ChronoBins (27.50) and MDD-Glyphs (27.75). The error bars denote the standard deviation. All values are considerably below average compared to the reference (orange bar) immersive devices. This indicates that despite the introduction of new technology and visualization metaphors, the domain experts have experienced a relatively low workload overall when using our framework. Additional valuable insights were gained by examining the individual categories, which were later supported by the interview. The MDD-Glyphs chart showed

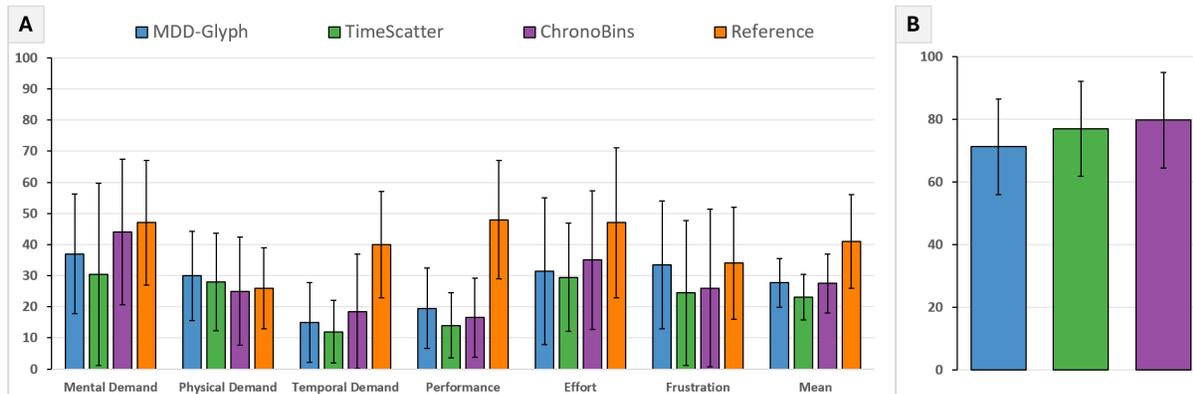
the highest scores for physical demand (30) and frustration (33.5). This may be attributed to its role as a primary interaction tool, as well as its novel immersive presentation and sophisticated color scheme. The overview generated by the TimeScatter visualization is reflected in the lowest frustration score (24.5). Despite this reasonably good rating, the ChronoBins visualization has the highest score for Mental Demand (44), probably due to the wealth of analysis options it offers. The combination of individual charts according to attributes and the selection of specific bins for display in the spatial representation required further familiarisation. Overall, the techniques performed well in terms of temporal demand and performance. This suggests that participants were able to obtain the desired results in a reasonable amount of time, which is crucial for exploratory data analysis.

As can be seen in Figure 9 B, SUS revealed the best usability for ChronoBins (79.75 = A-), followed by TimeScatter (77 = B) and by a small margin MDD-Glyphs (71.25 = C+). When comparing our framework's scores to those of an not acceptable product (< 51.7) [BKM09], there are strong indications that immersive analysis is applicable for real world industrial applications. A closer look at the specific SUS questions (see [Bro96]) revealed additional information about the presented visualization techniques. The MDD-Glyphs chart produced the highest score of all tasks in questions SQ5 (integration) and SQ6 (consistency), showing that the consistent integration of the glyph (rectangle) idiom was well received. Overall, however, this method scored the lowest because, supported by the Nasa TLX score, the interaction and analysis options were initially complex. The TimeScatter chart scores well in SQ2 (complexity) and SQ7 (ease of learning), indicating that the simple visualization allows for quick understanding and use of the chart. The ChronoBins visualization had the best SUS rating across all tasks. In particular, SQ8 (convenience), SQ9 (confidence) and SQ10 (ease of use) show that participants found the tool intuitive and enjoyed using it.

The general questionnaire reflects our experience about the receptivity to working with AR. The average response (4.3) to interest in working with AR is "Somewhat Agree" based on the individual questions: "I think I would like to start working more in AR" (4.3), "The embodied interaction can facilitate my work" (4.2), "I think the workflow in the application can be a support for my work" (4.4). The results of the questions on possible health issues resulted on average (1.6) in "Somewhat Disagree" according to the questions: "I felt general discomfort using the application" (1.4), "I felt eyestrain using the application" (2.3), "I felt headache using the application" (1.2).

### 6.2. Insights

Overall, the results of the evaluations and the interview show that the MDD-Glyphs is a promising technique. Participants said "I like not having to use a menu [for switchin between charts]" and "It is convenient to see all the characteristics of the fibres at once". Due to its seamless design as an orientation-dependent visualization, the transition from MDD-Glyphs to TimeScatter was well received. Others said, "It is quite difficult at first to know how to read the chart [MDD-Glyphs] and what gestures you can perform on it", suggesting a steeper initial learning curve. Further feedback



**Figure 9:** Each participant's responses on the (A) NASA-TLX evaluation and (B) SUS evaluation on each prototype. For the SUS, higher values are better; for the NASA-TLX, the order is reversed (lower is better). Error bars denote the standard deviation.

was provided on the user interface and additional utility features, such as automatic alignment of charts on desks and sorting of spatial representations by time step or name instead of loading order. One interesting comment was *"I am used to looking at 2D sectional views, so it would be great to be able to see these alongside the volume"* and to add a coordinate system in the spatial view to give a *"sense of scale"*. The ChronoBins display in particular received a lot of positive feedback for its combination of trend analysis and exploration of changes in the spatial representation. The experts would like to see more visualization techniques, including *"highlighting only fibres that have changed"* and *"semi-transparent switching of unchanged fibres to allow overlaying of volumes"*. With the ChronoBins display, artifacts in the fibre characterisation pipeline could also be easily detected, in which the number of fibres increased after fibre breaking but then decreased again.

With the results from the Nasa TLX and SUS questionnaires, we were able to evaluate the perceived usability and intuitiveness of an immersive material analysis as stated in (Q1). The positive scores show that the location-independent analysis and embodied navigation in our frameworks's immersive environment were well received, indicating that domain goal G1 was achieved. The menu-less switching between visualization techniques through viewpoint and interaction provided an intuitive workflow that took a few minutes to get used to. Navigating and exploring the data showed high usability and low workload. The suitability of our framework's AR visualization techniques on the interpretation and comprehension of complex data was identified through feedback received in the interview and during the study using the think-aloud protocol. Our novel immersive visualisation techniques enabled the experts to improve the exploration of the material data and enhanced their understanding of the time-dependent changes in the complex distributions of the attributes, which positively answered research question (Q2). The compact presentation and free arrangement of the diagrams facilitated the identification of correlations. In particular, highlighting temporal changes in the spatial volume improved the ability to identify certain patterns, required by domain goal (G3). Feedback suggested that immersive exploration also increased engagement.

## 7. Conclusions & Future Work

In this work, we have presented a novel immersive analysis tool applied to a real-world challenge in materials science. Our novel immersive AR framework, is designed to support experts in their cognitively demanding task of characterising materials, such as fibre-reinforced composites. Our tool supports the interactive analysis and comparison of multidimensional abstract and spatial data. We have presented three new visualization techniques, each revealing different aspects of the data and allowing users to explore them. Experts can test hypotheses, as well as detect and understand changes and defects in the material, using the spatial representation combined with our three novel visualization techniques. MDD-Glyphs charts are used to view many distributions simultaneously. TimeScatter visualization provides a quick view of temporal patterns. Finally, ChronoBins are effectively used to compare the changes in values between different time steps and look at the attributes value ranges in detail. Switching between representations via orientation-dependent visualizations and intuitive interaction within the charts ensures a seamless and menu-free user experience. To evaluate the potential of an immersive framework in this domain, we conducted a qualitative study with materials experts to test our methods. The results of the SUS and Nasa-TLX questionnaires indicate that analyzing distributions in immersive environments can be done with low workload. Specifically, the ChronoBins visualization, which allows for analysis of time-varying abstract data including spatial volumes, was well received and demonstrated high usability. The feedback received during the interviews has provided valuable information on how our framework, and immersive material analysis process as a whole, can be improved in the future. Since our techniques primarily operate on distributions of attributes, which can have temporal variations, their applicability extends far beyond the field of materials analysis. For instance, domains with heterogeneous data that evolve over time, such as climate science, bioinformatics, economics and social sciences, could greatly benefit from our approach.

Although we developed our framework with familiar visualization idioms in mind, there were still requests to optionally display traditional methods such as 2D slice images of the original spatial

data. At the same time, a major advantage of the AR framework was the ability to continue using traditional desktop environments in parallel with our framework. Future work should therefore focus on making the transition between familiar expert tools and new immersive applications more gradual and allow the use of familiar methods in order to maintain acceptance in the respective domains. Additionally, we aim to increase interaction with spatial representations and offer a range of model-based surface representations to test our techniques in other domains. Another promising approach is to integrate more efficient rendering methods to enable more precise analysis of region of interest scans at higher resolutions for defect identification and analysis. Finally, we would like to conduct a quantitative study comparing our visualization techniques with appropriate traditional 2D and 3D diagrams to determine differences in completion time and accuracy.

The encouraging feedback for our novel AR framework, indicates that this form of analysis is of interest to experts in industry and research, and offers potential for immersive analytics in various scenarios, such as the inspection of batteries, material recycling, pharmaceutical research and more. Our research highlights the potential of our framework to leverage the users spatial cognition for more effective visualization of abstract and spatial data, providing new insights into material characterization and quality control.

## 8. Acknowledgements

The research leading to these results has received funding by research subsidies granted by the government of Upper Austria within the program line "Dissertationsprogramm der FH OÖ", grant no. 881298 "AugmeNDT" and grant no. 881309 "COM-PARE".

## References

- [AMST11] AIGNER W., MIKSCH S., SCHUMANN H., TOMINSKI C.: *Visualization of Time-Oriented Data*. Springer London, 2011. doi:10.1007/978-0-85729-079-3. 5
- [BCBM18] BILLINGHURST M., CORDEIL M., BEZERIANOS A., MARGOLIS T.: *Collaborative Immersive Analytics*. Springer International Publishing, Cham, 2018, ch. 8, pp. 221–257. URL: [https://doi.org/10.1007/978-3-030-01388-2\\_8](https://doi.org/10.1007/978-3-030-01388-2_8), doi:10.1007/978-3-030-01388-2\_8. 2
- [BCK\*23] BOORBOOR S., CASTELLANA M. S., KIM Y., CHEN Z., BEYER J., PFISTER H., KAUFMAN A. E.: Voxar: Adaptive visualization of volume rendered objects in optical see-through augmented reality. *IEEE Transactions on Visualization and Computer Graphics* (2023), 1–12. doi:10.1109/tvcg.2023.3340770. 3
- [BDD19] BAZAN E., DOKLÁDAL P., DOKLADALOVA E.: Quantitative Analysis of Similarity Measures of Distributions. In *British Machine Vision Conference (BMVC)* (Cardiff, United Kingdom, Sept. 2019). URL: <https://hal.science/hal-02299826>. 8
- [BDL\*20] BLUMENSCHNEIN M., DEBBELER L. J., LAGES N. C., RENNERT B., KEIM D. A., EL-ASSADY M.: v-plots: Designing hybrid charts for the comparative analysis of data distributions. *Computer Graphics Forum* 39, 3 (June 2020), 565–577. doi:10.1111/cgf.14002. 5, 6
- [BKM09] BANGOR A., KORTUM P., MILLER J.: Determining what individual sus scores mean: adding an adjective rating scale. *J. Usability Studies* 4, 3 (may 2009), 114–123. URL: <https://dl.acm.org/doi/10.5555/2835587.2835589>. 10
- [BKS22] BOK J., KIM B., SEO J.: Augmenting parallel coordinates plots with color-coded stacked histograms. *IEEE Transactions on Visualization and Computer Graphics* 28, 7 (July 2022), 2563–2576. doi:10.1109/tvcg.2020.3038446. 8
- [BM13] BREHMER M., MUNZNER T.: A multi-level typology of abstract visualization tasks. *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (Dec. 2013), 2376–2385. doi:10.1109/tvcg.2013.124. 4, 5
- [Bro96] BROOKE J.: *SUS – a quick and dirty usability scale*. 01 1996, pp. 189–194. 10
- [CBC\*20] CORDEIL M., BACH B., CUNNINGHAM A., MONTOYA B., SMITH R. T., THOMAS B. H., DWYER T.: Embodied axes: Tangible, actuated interaction for 3d augmented reality data spaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (apr 2020), ACM. doi:10.1145/3313831.3376613. 3
- [CCB\*19] CORDEIL M., CUNNINGHAM A., BACH B., HURTER C., THOMAS B. H., MARRIOTT K., DWYER T.: IatK: An immersive analytics toolkit. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)* (2019), pp. 200–209. doi:10.1109/VR.2019.8797978. 3
- [CDH\*19] CAVALLO M., DOLAKIA M., HAVLENA M., OCHELTREE K., PODLASECK M.: Immersive insights: A hybrid analytics system for Collaborative exploratory data analysis. In *25th ACM Symposium on Virtual Reality Software and Technology* (Nov. 2019), ACM. doi:10.1145/3359996.3364242. 5
- [Cha08] CHA S.-H.: Taxonomy of nominal type histogram distance measures. In *Proceedings of the American Conference on Applied Mathematics* (Stevens Point, Wisconsin, USA, 2008), MATH'08, World Scientific and Engineering Academy and Society (WSEAS), p. 325–330. 7
- [CMH18] CORRELL M., MORITZ D., HEER J.: Value-suppressing uncertainty palettes. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (apr 2018), ACM. doi:10.1145/3173574.3174216. 6
- [DMI\*18] DWYER T., MARRIOTT K., ISENBERG T., KLEIN K., RICHE N., SCHREIBER F., STUERZLINGER W., THOMAS B. H.: *Immersive Analytics: An Introduction*. Springer International Publishing, Cham, 2018, ch. 1, pp. 1–23. URL: [https://doi.org/10.1007/978-3-030-01388-2\\_1](https://doi.org/10.1007/978-3-030-01388-2_1), doi:10.1007/978-3-030-01388-2\_1. 2
- [EAB\*20] EVANGELISTA A., ARDITO L., BOCCACCIO A., FIORENTINO M., PETRUZZELLI A. M., UVA A. E.: Unveiling the technological trends of augmented reality: A patent analysis. *Computers in Industry* 118 (June 2020), 103221. doi:10.1016/j.compind.2020.103221. 2, 3
- [EBC\*21] ENS B., BACH B., CORDEIL M., ENGELKE U., SERRANO M., WILLETT W., PROUZEAU A., ANTHES C., BÜSCHEL W., DUNNE C., DWYER T., GRUBERT J., HAGA J. H., KIRSHENBAUM N., KOBAYASHI D., LIN T., OLAOSEBIKAN M., POINTECKER F., SAFFO D., SAQUIB N., SCHMALSTIEG D., SZAFIR D. A., WHITLOCK M., YANG Y.: Grand challenges in immersive analytics. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, May 2021), ACM, pp. 8–13. URL: <https://prism.ucalgary.ca/handle/1880/112984>, doi:10.1145/3411764.3446866. 2, 3, 8
- [FAP\*22] FRÖHLER B., ANTHES C., POINTECKER F., FRIEDL J., SCHWAJDA D., RIEGLER A., TRIPATHI S., HOLZMANN C., BRUNNER M., JODLBAUER H., JETTER H.-C., HEINZL C.: A survey on cross-virtuality analytics. *Computer Graphics Forum* 41, 1 (Feb. 2022), 465–494. doi:10.1111/cgf.14447. 3
- [FP19] FONNET A., PRIE Y.: Survey of immersive analytics. *IEEE Transactions on Visualization and Computer Graphics* 27, 3 (Mar. 2019), 2101–2122. doi:10.1109/tvcg.2019.2929033. 3
- [FPG\*19] FERRAGUTI F., PINI F., GALE T., MESSMER F., STORCHI C., LEALI F., FANTUZZI C.: Augmented reality based approach for on-line quality assessment of polished surfaces. *Robotics and Computer-*

- Integrated Manufacturing* 59 (oct 2019), 158–167. doi:10.1016/j.rcim.2019.04.007. 3
- [FPS\*21] FRANCONERI S. L., PADILLA L. M., SHAH P., ZACKS J. M., HULLMAN J.: The science of visual data communication: What works. *Psychological Science in the Public Interest* 22, 3 (Dec. 2021), 110–161. doi:10.1177/15291006211051956. 6
- [FWS\*19] FRÖHLER B., WEISSENBOCK J., SCHIWARTH M., KASTNER J., HEINZL C.: open\_iA: A tool for processing and visual analysis of industrial computed tomography datasets. *Journal of Open Source Software* 4, 35 (Mar. 2019), 1185. doi:10.21105/joss.01185. 2
- [Gal24] GALL A.: Link to MARV implementation on GitHub. *Anonymised*, 2024. [Online; accessed 01-April-2024]. 9
- [GFH21] GALL A., FRÖHLER B., HEINZL C.: Cross virtuality analytics in materials sciences. In *ISS'21 Workshop Proceedings: "Transitional Interfaces in Mixed and Cross-Reality: A new frontier?"* (2021). URL: <https://dx.doi.org/10.18148/kops/352-2-wugxhv7d696t7>, doi:10.18148/kops/352-2-wugxhv7d696t7. 3
- [GGH21] GALL A., GRÖLLER E., HEINZL C.: ImNDT: Immersive Workspace for the Analysis of Multidimensional Material Data From Non-Destructive Testing. In *Proceedings of the 27th ACM Symposium on Virtual Reality Software and Technology* (New York, NY, USA, Dec. 2021), VRST '21, ACM, pp. 1–11. doi:10.1145/3489849.3489851. 3
- [Gre14] GREGG B.: Frequency Trails: Modes and Modality. <https://www.brendangregg.com/FrequencyTrails/modes.html>, 2014. [Online; accessed 01-April-2024]. 6
- [HASFY22] HO P. T., ALBAJEZ J. A., SANTOLARIA J., YAGÜE-FABRA J. A.: Study of augmented reality based manufacturing for further integration of quality control 4.0: A systematic literature review. *Applied Sciences* 12, 4 (Feb. 2022), 1961. 2, 3
- [HB03] HARROWER M., BREWER C. A.: ColorBrewer.org: An online tool for selecting colour schemes for maps. *The Cartographic Journal* 40, 1 (June 2003), 27–37. URL: <https://colorbrewer2.org/>, doi:10.1179/000870403235002042. 6, 8
- [Her21] HERTZUM M.: Reference values and subscale patterns for the task load index (tlx): a meta-analytic review. *Ergonomics* 64, 7 (Feb. 2021), 869–878. doi:10.1080/00140139.2021.1876927. 10
- [HGW\*24] HEIM A., GALL A., WALDNER M., GRÖLLER E., HEINZL C.: Accustripes: Visual exploration and comparison of univariate data distributions using color and binning. *Computers and Graphics* (Mar. 2024), 103906. doi:10.1016/j.cag.2024.103906. 5, 6, 8
- [HKL\*19] HEINZL C., KIRBY R. M., LOMOV S. V., REQUENA G., WESTERMANN R.: Visual Computing in Materials Sciences (Dagstuhl Seminar 19151). *Dagstuhl Reports* 9, 4 (2019), 1–42. URL: <http://drops.dagstuhl.de/opus/volltexte/2019/11302>, doi:10.4230/DagRep.9.4.1. 2
- [HRD\*19] HURTER C., RICHE N. H., DRUCKER S. M., CORDEIL M., ALLIGIER R., VUILLEMOT R.: FiberClay: Sculpting three dimensional trajectories to reveal structural insights. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019), 704–714. doi:10.1109/tvcg.2018.2865191. 3
- [HRGM14] HINCAPIÉ-RAMOS J. D., GUO X., MOGHADASIAN P., IRANI P.: Consumed endurance: a metric to quantify arm fatigue of mid-air interactions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Apr. 2014), CHI '14, ACM. doi:10.1145/2556288.2557130. 5
- [HRISI14] HINCAPIÉ-RAMOS J. D., IVANCHUK L., SRIDHARAN S. K., IRANI P.: SmartColor: Real-time color correction and contrast for optical see-through head-mounted displays. In *2014 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)* (sep 2014), IEEE. doi:10.1109/ismar.2014.6948426. 5
- [HS88] HART S. G., STAVELAND L. E.: *Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research*. Elsevier, 1988, pp. 139–183. doi:10.1016/s0166-4115(08)62386-9. 10
- [HS17] HEINZL C., STAPPEN S.: STAR: Visual Computing in Materials Science. *Computer Graphics Forum* 36, 3 (June 2017), 647–666. doi:10.1111/cgf.13214. 2
- [HXW20] HAYATPUR D., XIA H., WIGDOR D.: DataHop: Spatial data exploration in virtual reality. In *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* (Oct. 2020), ACM. doi:10.1145/3379337.3415878. 3
- [HZBR21] HUBENSCHMID S., ZAGERMANN J., BUTSCHER S., REITERER H.: Stream : Exploring the combination of spatially-aware tablets with augmented reality head-mounted displays for immersive analytics. In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI 2021)* (New York, 2021), ACM. doi:10.1145/3411764.3445298. 3
- [IM19] IDA N., MEYENDORF N. (Eds.): *Handbook of Advanced Nondestructive Evaluation*. Springer International Publishing, Cham, Switzerland, 2019. doi:10.1007/978-3-319-26553-7. 2
- [KFS\*22] KRAUS M., FUCHS J., SOMMER B., KLEIN K., ENGELKE U., KEIM D., SCHREIBER F.: Immersive analytics with abstract 3d visualizations: A survey. *Computer Graphics Forum* 41, 1 (Feb. 2022), 201–229. doi:10.1111/cgf.14430. 2
- [Kit24] KITWARE: Paraview Website. <https://www.paraview.org/desktop/>, 2024. [Online; accessed 01-April-2024]. 2
- [KKF\*21] KRAUS M., KLEIN K., FUCHS J., KEIM D. A., SCHREIBER F., SEDLMAIR M.: The value of immersive visualization. *IEEE Computer Graphics and Applications* 41, 4 (2021), 125–132. doi:10.1109/MCG.2021.3075258. 2
- [Koc13] KOCH I.: *Analysis of Multivariate and High-Dimensional Data*. Cambridge University Press, Dec. 2013. doi:10.1017/cbo9781139025805. 6
- [KWO\*20] KRAUS M., WEILER N., OELKE D., KEHRER J., KEIM D. A., FUCHS J.: The impact of immersion on cluster identification tasks. *IEEE Transactions on Visualization and Computer Graphics* 26, 1 (Jan. 2020), 525–535. doi:10.1109/tvcg.2019.2934395. 5
- [Lew18] LEWIS J. R.: The system usability scale: Past, present, and future. *International Journal of Human-Computer Interaction* 34, 7 (Mar. 2018), 577–590. doi:10.1080/10447318.2018.1455307. 10
- [LH18] LIU Y., HEER J.: Somewhere over the rainbow: An empirical assessment of quantitative colormaps. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Apr. 2018), CHI '18, ACM. doi:10.1145/3173574.3174172. 6
- [LJS21] LYI S., JO J., SEO J.: Comparative layouts revisited: Design space, guidelines, and future directions. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2021), 1525–1535. doi:10.1109/TVCG.2020.3030419. 5
- [LKK17] LEE S., KIM S.-H., KWON B. C.: Vlat: Development of a visualization literacy assessment test. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (jan 2017), 551–560. doi:10.1109/tvcg.2016.2598920. 4
- [MCH\*18] MARRIOTT K., CHEN J., HLAWATSCH M., ITOH T., NACENTA M. A., REINA G., STUERZLINGER W.: *Just 5 Questions: Toward a Design Framework for Immersive Analytics*. Springer International Publishing, 2018, pp. 259–288. doi:10.1007/978-3-030-01388-2\_9. 3, 4
- [ME20] MASOOD T., EGGER J.: Adopting augmented reality in the age of industrial digitalisation. *Computers in Industry* 115 (Feb. 2020), 103112. doi:10.1016/j.compind.2019.07.002. 2
- [Mic24] MICROSOFT: Mixed Reality Toolkit - Unity. <https://github.com/Microsoft/MixedRealityToolkit-Unity>, 2024. [Online; accessed 01-April-2024]. 9
- [MSJ\*22] MAURER J., SALABERGER D., JERABEK M., KASTNER J.,

- MAJOR Z.: Quantitative investigation of local strain and defect formation in short glass fibre reinforced polymers using x-ray computed tomography. *Nondestructive Testing and Evaluation* 37, 5 (May 2022), 582–600. doi:10.1080/10589759.2022.2075865. 9
- [NPJ09] NAIK N., PATIL S., JOSHI M.: A scale adaptive tracker using hybrid color histogram matching scheme. In *2009 Second International Conference on Emerging Trends in Engineering and Technology* (2009), IEEE. doi:10.1109/ictet.2009.19. 8
- [PIL\*18] PRATT P., IVES M., LAWTON G., SIMMONS J., RADEV N., SPYROPOULOU L., AMIRAS D.: Through the HoloLens™ looking glass: augmented reality for extremity reconstruction surgery using 3d vascular models with perforating vessels. *European Radiology Experimental* 2, 1 (Jan. 2018). doi:10.1186/s41747-017-0033-2. 3
- [RBLB19] RODRIGUES A. M. B., BARBOSA G. D. J., LOPES H., BARBOSA S. D. J.: Comparing the effectiveness of visualizations of different data distributions. In *2019 32nd SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)* (oct 2019), IEEE. doi:10.1109/sibgrapi.2019.00020. 5, 6
- [RPML19] RAJAK D., PAGAR D., MENEZES P., LINUL E.: Fiber-reinforced polymer composites: Manufacturing, properties, and applications. *Polymers* 11, 10 (Oct. 2019), 1667. doi:10.3390/polym11101667. 2
- [SBC\*23] SAFFO D., BARTOLOMEO S. D., CRNOVRSANIN T., SOUTH L., RAYNOR J., YILDIRIM C., DUNNE C.: Unraveling the design space of immersive analytics: A systematic review. *IEEE Transactions on Visualization and Computer Graphics* (2023), 1–12. doi:10.1109/TVCG.2023.3327368. 2, 3
- [SCT\*22] SATHIADI K. A., CUNNINGHAM A., THOMAS B. H., DROGEMULLER A., ODI A., PATEL N., ASTON C., SMITH R. T.: Augmented scale models: Presenting multivariate data around physical scale models in augmented reality. In *2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)* (Oct. 2022), IEEE. doi:10.1109/ismar55827.2022.00019. 3
- [SD21] SATKOWSKI M., DACHSELT R.: Investigating the impact of real-world environments on the perception of 2d visualizations in augmented reality. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (may 2021), ACM. doi:10.1145/3411764.3445330. 3
- [SED19] SAKET B., ENDERT A., DEMIRALP C.: Task-based effectiveness of basic visualizations. *IEEE Transactions on Visualization and Computer Graphics* 25, 7 (jul 2019), 2505–2512. doi:10.1109/tvcg.2018.2829750. 4, 5
- [SKB18] SCHICKERT M., KOCH C., BONITZ F.: Prospects for integrating augmented reality visualization of nondestructive testing results into model-based infrastructure inspection. In *NDE/NDT for Highways & Bridges: SMT 2018* (2018), ASNT, pp. 214–223. URL: <https://api.semanticscholar.org/CorpusID:86808534>. 3
- [SKGM21] SARDANA D., KAHU S. Y., GRAČANIN D., MATKOVIĆ K.: Multi-modal data exploration in a mixed reality environment using coordinated multiple views. In *Human Interface and the Management of Information. Information Presentation and Visualization*. Springer International Publishing, 2021, pp. 337–356. doi:10.1007/978-3-030-78321-1\_26. 3
- [SKK\*11] SALABERGER D., KANNAPPAN K. A., KASTNER J., REUSSNER J., AUINGER T.: Evaluation of computed tomography data from fibre reinforced polymers to determine fibre length distribution. *International Polymer Processing* 26, 3 (2011), 283–291. doi:10.3139/217.2441. 4
- [SLC\*19] SICAT R., LI J., CHOI J., CORDEIL M., JEONG W.-K., BACH B., PFISTER H.: DXR: A toolkit for building immersive data visualizations. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019), 715–725. doi:10.1109/tvcg.2018.2865152. 3
- [SMM12] SEDLMAIR M., MEYER M., MUNZNER T.: Design study methodology: Reflections from the trenches and the stacks. *IEEE Transactions on Visualization and Computer Graphics* 18, 12 (Dec. 2012), 2431–2440. doi:10.1109/tvcg.2012.213. 4
- [SMS21] SAHANN R., MULLER T., SCHMIDT J.: Histogram binning revisited with a focus on human perception. In *2021 IEEE Visualization Conference (VIS)* (Oct. 2021), IEEE. doi:10.1109/vis49827.2021.9623301. 6
- [SS05] SEO J., SHNEIDERMAN B.: A rank-by-feature framework for interactive exploration of multidimensional data. *Information Visualization* 4, 2 (May 2005), 96–113. arXiv: <https://doi.org/10.1057/palgrave.ivs.9500091>, doi:10.1057/palgrave.ivs.9500091. 5, 6
- [SSS\*19] SHKARIN R., SHKARIN A., SHKARINA S., CECILIA A., SURMENEV R. A., SURMENEVA M. A., WEINHARDT V., BAUMBACH T., MIKUT R.: Quanfima: An open source python package for automated fiber analysis of biomaterials. *PLOS ONE* 14, 4 (Apr. 2019). doi:10.1371/journal.pone.0215137. 2
- [The24] THERMO FISHER SCIENTIFIC: 3d visualization & analysis software website. <https://www.thermofisher.com/at/en/home/electron-microscopy/products/software-em-3d-vis/avizo-software.html>, 2024. [Online; accessed 01-April-2024]. 2
- [TSK20] TADEJA S. K., SESHADRI P., KRISTENSSON P. O.: AeroVR: An immersive visualisation system for aerospace design and digital twinning in virtual reality. *The Aeronautical Journal* (June 2020), 1–21. doi:10.1017/aer.2020.49. 3
- [Uni24] UNITY U. T.: Unity Website. <https://unity.com/>, 2024. [Online; accessed 01-April-2024]. 9
- [Vol24] VOLUMEGRAPHICS: VGSTUDIO MAX Website. <https://www.volumegraphics.com/de/produkte.html>, 2024. [Online; accessed 01-April-2024]. 2
- [WDG\*19] WALDNER M., DIEHL A., GRACANIN D., SPLECHTNA R., DELRIEUX C., MATKOVIC K.: A comparison of radial and linear charts for visualizing daily patterns. *IEEE Transactions on Visualization and Computer Graphics* (2019), 1–1. doi:10.1109/tvcg.2019.2934784. 5
- [WZYW20] WANG S., ZHU D., YU H., WU Y.: Immersive WYSIWYG (what you see is what you get) volume visualization. doi:10.1109/pacificvis48177.2020.1001. 3
- [ZLL\*18] ZHOU F., LIN X., LIU C., ZHAO Y., XU P., REN L., XUE T., REN L.: A survey of visualization for smart manufacturing. *Journal of Visualization* 22, 2 (Nov. 2018), 419–435. doi:10.1007/s12650-018-0530-2. 2