Enhancing Public Safety with Digital Twins for Indoor Air Quality Monitoring by Non-Experts

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***Abstract*—Digital Twin technology has been used in many different domains to integrate disparate and complex data sources into a single, comprehensible system. A less explored field is monitoring indoor air quality and building efficiency by providing real-time visualization and spatially contextualized data in commercial buildings. Managers of commercial buildings often have little or no training in indoor air quality, heating ventilation and air conditioning systems (HVAC), or building efficiency. This makes it difficult for them to evaluate environmental and efficiency data, if such data are available. This study evaluates the effectiveness of Digital Twins in 2D Desktop and 3D Virtual Reality to support non-expert user engagement, data interpretation, and spatial understanding for indoor air quality and building efficiency analysis. Sensors were installed in a mixed-use office/light industrial space, with a system infrastructure that collects and stores historical data readings. A comparative study was conducted between i) a traditional web-based dashboard (the control condition), ii) a 2D, and iii) a Virtual Reality Digital Twin using a within-subject research design involving non-expert participants, to determine the efficacy levels of user engagement with the data presentation mechanisms of each system, their spatial understanding, and their ability to conduct data interpretation. The findings demonstrate that VR Digital Twin supports increased spatial awareness and understanding, immersion, and data discovery, and the 2D Digital Twin system provides clarity and accessibility for trend analysis. The study contributes by i) validating the role of Digital Twins for Indoor Air Quality; ii) exploring user perceptions on different Digital Twin mediums in terms of user engagement; and iii) highlighting the potential of Digital Twins for public safety, particularly in indoor environments.**

***Index Terms*—Digital Twins, eXtended Reality, Data visualization, Public Safety, Immersive Analytics**

I. Introduction

The COVID-19 pandemic clearly demonstrated the importance of Indoor Air Quality (IAQ), good ventilation and the dependence on heating, ventilation and cooling systems (HVAC) in buildings [1]. Unfortunately, IAQ is a complex topic that has typically been the domain of technical experts, such as industrial hygienists. While airflow within a building can be described with fluid dynamics, the underlying mathematics is complex, difficult to apply to real-world systems, and well beyond the abilities of most people. In addition, building HVAC systems vary significantly, based on building age, usage, variation between installations, local climate conditions, regional standards, and many other factors [2]. As a result, data analysis related to IAQ, and the efficiency of the related systems, is challenging. This problem is compounded by the fact that most building operators and facility managers have little formal training in HVAC and related systems. There is a clear need for granular, actionable, real-time data that helps building operators and building occupants meaningfully assess the performance of HVAC systems and a building's IAQ.

The concept of "Visual Analytics" has shown considerable promise in making data actionable. This refers to a method introduced two decades ago as the science of analytical reasoning facilitated by interactive visual interfaces [3]. While this definition does not specify the types of interface devices used in visual analysis systems, it has been noted that the capabilities of display and input devices significantly impact the user experience in such systems [4]. Visual analytics has broad applicability across multiple domains, including monitoring IAQ.

Recent advancements in eXtended Reality (XR - encompassing Virtual, Augmented and Mixed Reality hardware and software) have significantly enhanced data analytics tasks, offering modes for experiencing more immersive and interactive environments that enable users to engage with complex data in intuitive ways [5]. The use of XR and other interactive technologies has contributed toward the development of "Immersive Analytics", a growing research area focused on the use of advanced display and interaction technologies for analysing and interacting with data in immersive ways.

In recent years, Digital Twin (DT) technology has also become increasingly pervasive, and one application area with the potential to make a significant impact on public safety and public health is environmental quality management. A DT is a virtual replica that shadows a physical entities/system. A DT enables continuous monitoring, simulation, and optimization through a combination of real-time data, advanced visualizations, and analytics [6]. Although DTs have been successfully implemented in various sectors such as manufacturing, engineering, and healthcare, their application to IAQ management is still in its early stages. As with other application areas, DTs for IAQ can deliver analysis, simulation, and system optimization resulting in tangible gains in efficiency and public safety.

This paper investigates the potential of DT technology in supporting IAQ management. We examine whether DT and immersive environments presented in 2D and 3D VR formats can more effectively enable a layperson to make informed decisions when compared to more traditional approaches to data visualization. The aim is to explore the efficacy of different visualization modalities, testing how and if an immersive DT can contribute toward enhancing spatial awareness, user engagement, and overall comprehension of IAQ and building health. The goal is to explore whether DT technology can effectively support non-technical stakeholders in monitoring and identifying IAQ issues.

II. Background and Context

III. Digital Twins for Indoor Air Management

IAQ is a subset of Indoor Environment Quality (IEQ). IEQ has emerged as a critical factor affecting the health, comfort, and productivity of occupants in residential, commercial, and industrial buildings [7]. IEQ refers to the collection of factors, including thermal conditions, lighting, acoustics, and IAQ, that determine the environmental quality, healthiness, and overall well-being of a closed indoor space [8]. We spend more than 90% of our lives indoors, breathing the air within buildings [9]. According to the World Health Organization (WHO) [10], exposure to indoor pollutants is linked to a range of adverse health effects, including respiratory illnesses, cardiovascular diseases, and impaired cognitive function. The WHO publishes the 'WHO Guidelines for Indoor Air Quality: Selected Pollutants' offering guidance to reduce health risks from common indoor pollutants, and there are also several initiatives that publish guidelines regarding IAQ problems [11].

Gaining a comprehensive understanding of IAQ in buildings requires significant effort due to the complexity of the factors affecting IAQ. Indoor air pollution arises from a variety of sources, both indoor and outdoor, including common building materials, cleaning supplies, smoking, cooking, nearby traffic emissions and even the building occupants themselves. Sources and their impact also vary by season and can be affected by local weather conditions. There is also significant variation between buildings and conditions that fluctuate over time, making the identification process extremely complex [12]. A common way to support IAQ management practices is with Internet of Things (IoT) technology, specifically, sensors designed for environmental monitoring. Recent developments in IoT devices and their components have enabled increasing accuracy at lower cost. Commercial IAQ sensors can enable accurate and efficient daily monitoring of IAQ, thereby capturing the data needed to improve the energy efficiency, flexibility, and resilience of ventilation systems [12].

As noted previously, DTs show promise as a technology that can support efforts to manage IEQ, helping to drive the transition to smarter buildings with improved energy efficiency and healthier indoor environments [8]. *"A digital twin is a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making"* [13]. In DT technology, data is gathered from real-world sensors (IoT), processed using a variety of algorithms, and presented through a virtual model that serves as a digital replica, or twin, of a physical system or entity. The sensor data is directly mapped to the DT, mirroring the system's operation so that anyone viewing the DT can access near-real-time information about the physical system's state and performance, potentially providing more valuable data than directly observing the physical system itself [6]. DTs are used across various industries to monitor, simulate, and optimize operations. In multiple industries, DT technology is used to predict future performance, identify inefficiencies, and enable decision-makers to take actions to address or predict issues. DTs are particularly effective in complex systems as they provide ways to integrate disparate sources of information within a single visualization framework. This ability to visualize entities and real-time data, creating a digital representation of complex physical environments/elements/systems/processes, is a key function of a DT.

To date, DT technology has not been broadly applied to IEQ and there are still considerable knowledge gaps in approaches that holistically address IEQ, particularly in relation to thermal comfort and IAQ [8]. Several companies offer DT solutions for IEQ and building management. Examples include the *eDigiT2Life* project from Integrated Environmental Solutions [14], DT solutions from Johnson Controls [15], and the *TwinView* platform from Space Group [16]. Some DT solutions are also available for general facilities management from companies such as Bosch [17], Sensegreen [18] and Siemens [19]. However, these solutions generally target large, new smart buildings rather than the existing built environment.

A. Immersive Analytics and VR

The real-time visualization capability of DTs provides interactive and data-rich experiences. An increasingly common approach is to combine DTs with VR for immersive visualisation and analytics. Research in immersive analytics involves developing and evaluating novel interfaces and devices, and utilising metaphors and visualizations to support data understanding and decision-making. It is a highly multidisciplinary field, bringing together researchers from the fields of human-computer interaction, visual analytics, immersive technologies, computer graphics, and information visualization [4]. To support data visualization, multiple tools exist to support data exploration, interpretation and decision making. These tools are capable of maintaining and digitally representing data, allowing users to interact and manipulate information through human-computer interfaces to explore, analyse and interpret data and hypothesis on their own [20].

Immersive analytics go beyond traditional visual analytics methods, as detailed in the comprehensive survey by Marriott et al. [21], providing many opportunities for enhancing interaction and engagement in analytics, enabling more intuitive, collaborative, and multi-sensory experiences that support data interpretation and more effective decision-making. Such methods provide opportunities for *Situated Analytics* that link data analytics to physical objects, like products or tools, with practical uses in the workplace and everyday life, enabling personalised analytics based on physical context [22]. They support *Embodied Data Exploration* through touch, gestures, voice, and tangible interactions instead of traditional mouse and keyboard inputs, aiming to make data exploration more intuitive and engaging, in modes where the computer fades into the background, while still supporting analytics [23], [24]. Immersive analytics support in-person and remote *Collaboration*, both synchronously and/or asynchronously, facilitating collaboration in socially engaging and effective ways [25]. Furthermore, they allow the user to move beyond the desktop/tablet/screen experience, offering opportunities for *Spatial Immersion* that allows users to work within 3D spaces and interact with 2D, 2.5D, and 3D data visualizations in immersive and spatially oriented workspaces [26].Moreover, while traditional visual analytics focus on visual data, immersive analytics support *Multi-Sensory Presentation* modes that incorporate other senses, like audio, spatial exploration and touch, to provide additional or alternative information to enhance data interpretation, especially when visual information alone is insufficient [27]. Lastly, such methods provide opportunities for immersive narrative visualizations to support *Increased Engagement* through data-driven decision-making [28]

Some of the technologies commonly used for immersive analytics are touch surfaces, sensors, and immersive VR and AR among other emerging digital tools and natural user interfaces [4]. In VR and 3D data visualization in particular, user interface researchers and developers often concentrate on core challenges such as improved rendering techniques, achieving reliable gesture recognition, head-tracking, and other low-level technical areas [4]. One of the key affordances of VR is the users' feeling of 'presence' and 'immersion'. Immersion is defined as "*the degree which the range of sensory channel is engaged by the virtual simulation*" [29], referring to the user's engagement with the system that leads to a flow state mostly driven by sensory immersion. Presence is defined as "the subjective experience of being in an environment when physically situated in another" [30](p. 255). This enables users to develop the psychological perception of 'being in' the virtual environment rather than the physical one [31], [32]. Although terms like digitally mediated 'presence' and 'immersion' are frequently used interchangeably [33], they are different [34], [35]. Presence refers to the subjective experience, whereas immersion pertains to the technological effect of replacing real sensory stimuli with synthetic ones; in simple words, the greater the replacement, the higher the level of immersion [36], [37]. Immersion thus relates to the technical elements of a virtual environment that support the user's sense of presence. Presence is influenced by immersion but ultimately depends on how the user perceives and responds to the virtual experience.

An additional key benefit of VR is the ability to provide realistic (or unrealistic), immersive experiences that enhance spatial understanding. VR offers depth cues, such as stereo images and head tracking, allowing users to leverage their natural ability to perceive stereopsis and motion parallax. VR can also reduce destruction and information clutter, which is common in computer desktops filled with icons and notifications, enabling the virtual environments to become easier to understand. This offers increased peripheral awareness and greater information bandwidth, further improving the user experience [38]. Through these affordances, VR can help to develop engaging interactive visualization experiences that would support users' needs for understanding and engaging with data. User engagement is a complex concept that is not directly observable but can be assessed through various indicators, combining emotional, cognitive, and behavioural components. This construct has been explored in various disciplines such as education, games, and human-computer interaction, each offering different perspectives on what constitutes engagement. Key characteristics include intention (users should have an initial commitment to interact), autonomy (interaction should be voluntary), purpose (engagement should be driven by personal interest), time (users should spend a meaningful amount of time interacting), and outcome gained from interacting with visualization (users should gain more than just superficial information) [39]. Considering that when coupled with DT technology, VR has the potentials to to offer an ideal combination of immersion and presence while supporting interactive, spacially aware analytics, such approach makes it potentially valuable in making complex data accessible to non-expert audiences.

IV. Research Methodology

A. Problem Statement

As noted previously, IAQ is a complex and multifaceted problem space. Historically, interpreting data and determining appropriate remedial actions for a given building has relied on a combination of intensive data gathering and significant technical expertise. The advent of lower cost IoT devices for environmental sensing has made data collection significantly easier, but the issues of analysis and interpretation remain. The opportunity presented by VR and immersive analytics is to make analysis and interpretation more accessible to the layperson. In particular, leveraging the affordances of DTs and VR for immersive data analytics has the potential to make the collected data understandable and actionable for someone responsible for building operation who has not received deep technical training, and does not possess a detailed understanding of airflow, industrial hygiene, HVAC systems and other related topics.

This paper aims to explore the efficacy of DTs for monitoring IAQ, through a comparative investigation of a web-based visualization dashboard using traditional charts, a web-based 2D visualization (a simplified DT), and a 3D DT experienced in VR. To explore this, a comparative experimental study was conducted assessing the users' ability to interpret data and understand the spatial environment of an existing building within the context of environmental conditions and IAQ, by experiencing the three different modalities previously outlined.

B. Research Questions

The research questions driving this study focus on exploring effectiveness in terms of user engagement with data visualization, efficient data interpretation, and spatial understanding for three different modalities: i) a traditional web-based visualization dashboard, ii) a simplified DT in 2D (2D DT), and iii) an immersive 3D DT experienced in VR (VR DT).

RQ1: How does user engagement differ between the web-based dashboard, the 2D DT, and the VR DT in data visualization tasks? This question investigates users' perceptions towards the data visualisation mechanisms in terms of Aesthetics, Captivation, Challenge, Control, Discovery, Exploration, Creativity, Attention, Interest, Novelty, and Autotelism; which are factors relevant to user engagement with visual data. The goal is to determine which modality offers the most engaging user experience during data visualization exploration tasks.

RQ2: To what extent do the three modalities support users' ability to interpret data efficiently? This question compares users' ease of understanding environmental data and its perceived usefulness between the three conditions, assessing whether spatial and immersive interfaces improve data interpretation compared to the traditional data visualization dashboard.

RQ3: How do the three modalities differ in their impact on users' spatial understanding of environmental conditions within the building?; exploring how effectively each approach supports users in visualizing data spatially, understanding the building layout, and identifying the locations of areas with poor environmental quality.

To address these research questions, a comparative study employing a within-subject design was conducted. Study participants interacted with the three distinct conditions for data visualization and interpretation of the environment, performing a series of predefined data analysis tasks.

C. Experimental Design

1) System Design and Architecture: The development of the DT systems began with the deployment of Nosy sensors [40] in a two floor light industrial mixed office space building located in New England, USA. Sensors were installed in the corridors throughout the building, with each sensor collecting data every five minutes. The collected data includes temperature, relative humidity and total volatile organic chemicals (tVOC) as a measure of indoor air quality. The sensors are battery powered, using a Bluetooth mesh network to transmit their data to a local time-series database for storage. The data is also replicated to the cloud for additional processing and analysis. Traditional chart-based data visualizations are created using Grafana, an open source analytics and interactive visualization web-based dashboard system (See Fig. 1).

Using the time-series data server, the research team at the University of Central Lancashire, Cyprus (UCLan Cyprus) have developed a simplified 2D DT web based platform that displays data within a geographical information system (GIS). Using a combination of color-coding and time-based visualization, the platform displays the sensor locations with

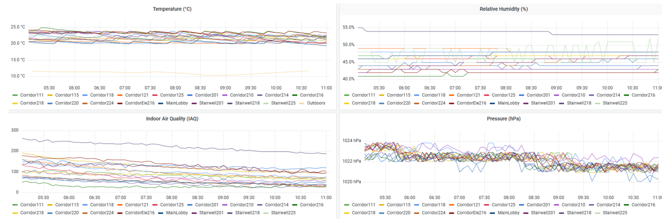

Fig. 1. The Grafana Web-Based Visualization Dashboard

data collected by the sensors overlaid on the 2D layout of the building (see Fig 2). This tool allows users to monitor and interpret the environmental conditions in near real-time and review historical data for any given time period. The platform also produces summary reports for each calendar month (See Fig. 3.). These reports use data from all the sensors within a building to assess multiple factors, such as temperature, relative humidity, IAQ and CO_2 levels.

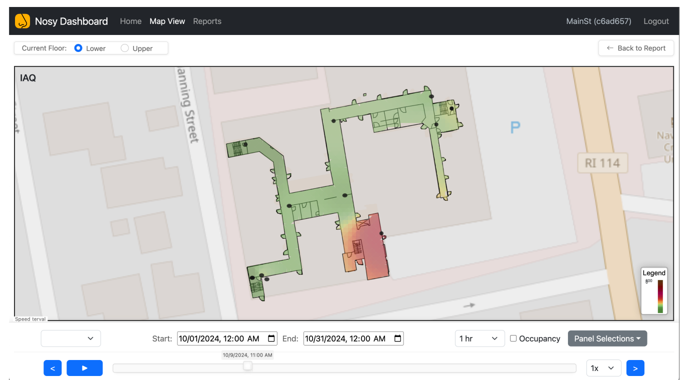

Fig. 2. The 2-Dimensional Digital Twin

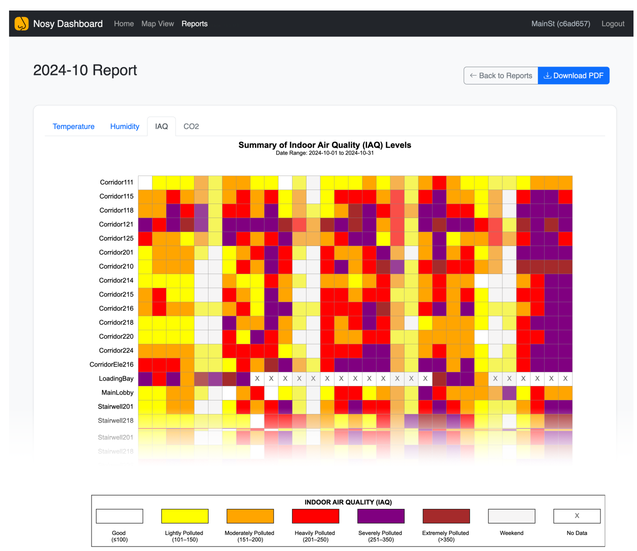

Fig. 3. IAQ Report Generated in the 2D DT System

In parallel, a VR DT was developed using Unity3D, featuring a digital representation of the actual building. The 3D model for the DT was captured with a Matterport camera, which generated a detailed 3D scan of the building interior. The 3D model was simplified and imported into Unity, where the building's virtual model was created. To enable real-time data updates in the VR environment, data is retrieved via a REST API and imported into Unity, where it is visualized through different techniques such as graphs, color-coding, heatmaps, and overlays. The VR environment allows users visualize the environment through an isometric camera (Fig. 4), and by navigating through the building and interacting with the data via a user interface panel (Fig. 5).

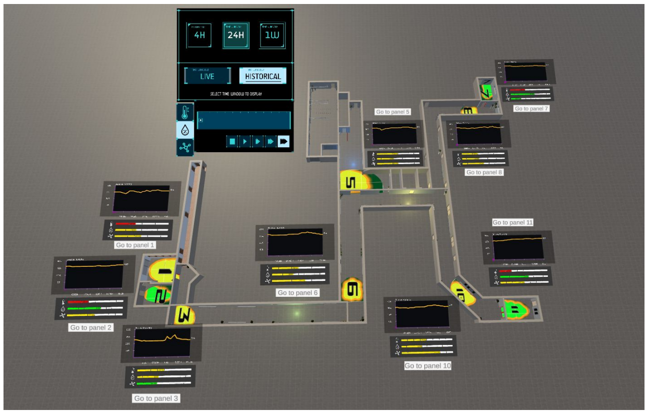

Fig. 4. Isometric View of the Environment Through the VR DT

Fig. 5. Example View from the Environment in the VR DT

The DT system architecture is divided into multiple layers, each performing a specific function: data ingestion; data processing; 3D model and visualization; and user interaction (Fig. 6). The data ingestion layer fetches the environmental data from the time-series database via REST API calls, and the data processing layer validates and associates the sensor data with specific locations in the 3D model. The 3D model and visualization layer manages the real-time updates in Unity, rendering the 3D building and displaying data interactively. The user interface facilitates user interaction with the VR environment, allowing to engage with the presented data and explore the building in VR.

2) Data Collection Instruments: To examine the effect of each modality on user engagement, data interpretation, and spatial understanding, we evaluated a number of factors

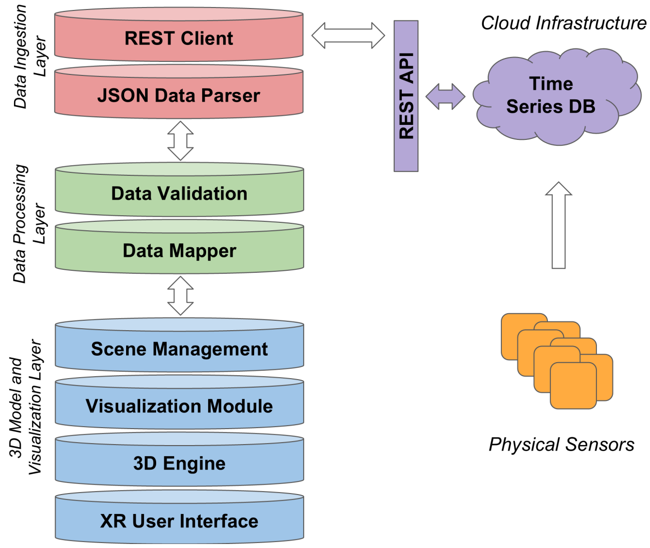

Fig. 6. Overview of DT System Architecture

relevant to interaction with complex spatial data to support informed decisions related to IAQ. To measure and compare the levels of user engagement with the three modalities, we employed the '*VisEngage*' questionnaire developed by Hung and Parsons [20]. VisEngage allows to measure how users emotionally and cognitively connect with visualizations, providing insights into the effectiveness of visualizations beyond just usability and performance. VisEngage is measured on a 7-point Likert scale and assesses 11 engagement characteristics (Aesthetics, Captivation, Challenge, Control, Discovery, Exploration, Creativity, Attention, Interest, Novelty, and Autotelism). For each characteristic, VisEngage authors designed two specific items, totalling 22 items, providing insights into one of the 11 engagement categories for a thorough evaluation of distinct user engagement dimensions. The highest aggregated score that can be achieved is 154.

To assess users' data interpretation and spatial understanding in the context of environmental conditions within the building, we formulated a questionnaire that captures their overall experience. The questionnaire includes questions related to the identification of areas with poor air quality, spatial layout, and data distribution understanding using the questions presented in Table III. Both questionnaires were rated in a 7-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (7). Data on participants' demographics was also collected using a pre-experiment questionnaire, to capture their gender, age, field of work, and previous experience with computers and VR, IAQ monitoring systems, data analytics tools, and interpretation of environmental data.

3) Experimental Procedures: To conduct this comparative investigation, a general call for participation was announced at UCLan Cyprus. Prior to the participants interaction with any of the study materials, they were briefed of the purpose of this study, and their informed consent was sought. Participants were requested to complete the pre-experiment questionnaire, and were given a scenario requiring them to assume the role of a building manager responsible for monitoring the indoor environment across various areas of a building. Their goal was to analyze real-time and historical data to identify areas with problematic environmental conditions, such as temperature, humidity, and IAQ, in order to report these issues to the senior management. Participants were first exposed to the traditional charts used by the web-dashboard tool, followed by the 2D DT, and lastly in the 3D VR DT. In each system, they were offered an initial orientation tutorial to understand the feature of each system. They were then assigned a simple task (identifying the current temperature of the main lobby area) to familiarise them with the system. Once this orientation was completed, participants were asked to perform a series of tasks designed to evaluate their ability to interpret environmental data and understand spatial relationships within the three systems. The same tasks were completed across all three systems, in the following order: 1) web-based Dashboard, 2) 2D DT, and 3) VR DT. We chose this sequence to minimise any potential 'wow effect' that VR technology may had on users. The first task required to analyze real-time data to identify areas with the highest current temperature and lowest IAQ. The second task required to review data for the previous 8 hours to find the areas with the highest recorded temperature and humidity. The final task required to review data for the previous 24 hours to find the area with the lowest air quality, and humidity levels above 65%. In each task, areas of the building with outlier measurements making the task trivial were excluded, for instance we excluded the corridors where temperature, humidity and IAQ measurements were constantly poor.

The experimental session for each participant lasted between 30-45 minutes with short 5 minute breaks provided between the different systems to prevent fatigue. During the sessions, a researcher supported participants when needed. Additional guidance was provided if their answers were incorrect. After completing their tasks in each system, participants completed the VisEngage questionnaire, and rated their perceptions about their system experience. At the end of the study, participants also completed the post-experiment experience questionnaire. The same measurements dataset was used across all systems. For the web dashboard and the 2D DT, participants used Google Chrome web browser on a medium to high end PC. For the VR DT, participants used the Meta Quest 2 head mounted display in tethered mode on a medium to high end PC equiped with an Intel Core i7-10700K CPU, 2.9 GHz, NVidia 3060 RTX GPU, and 32GB of DDR4 RAM.

4) Participants: The study participants were drawn from the IT community, including university students and professionals, none of whom were experts in IAQ management or related building systems. This was an intentional choice to evaluate the efficacy of the visualization systems being tested for non-experts. The use of non-experts ensured that the systems were assessed on the basis of the participants' ability to effectively understand the environmental data and spatial relationships using the systems provided, rather than relying on existing technical knowledge. For the sake of clarity, in real world usage, non-experts could include facility managers, business managers, policymakers, educators, and even building occupants. In practice, buildings are typically managed by individuals that are not experts in IAQ or HVAC systems. These individuals often need to interpret data and make informed decisions, but as discussed previously, they do not have advanced technical expertise in IAQ and HVAC systems, or prior experience with complex data visualization platforms. Experts, from HVAC contractors to industrial hygienists, are only brought in to a building when issues have become severe and obvious, such as the clear presence of health hazards (smells, mould, obvious damp patches), or system failure.

Our evaluation study included 23 participants (18 Male, 5 Female) between 18 and 54 years old (60% between 18-24, 18% between 25-34, 9% between 35-44, and 13% between 45-54). Most participants were very experienced with the use of computers (Mean=4.39, SD=84; where 5=very experienced). Participants reported varying levels of familiarity with VR, where 17.4% indicated they had no previous experience, 21.7% reported limited experience, 21.7% described themselves as somewhat experienced, 26.1%, indicated good experience with VR, and 13.0% rated themselves as very experienced. Regarding domain-specific expertise, participants reported low familiarity with IAQ management (Mean=1.83, SD=1.15) and interpreting environmental data (Mean=2.65, SD=1.46). Additionally, their frequency of using dashboards or data visualization tools was moderate (Mean=3.83, SD=1.67; where 7=very frequent use).

V. Results

Prior to conducting any data analyses, the degree of normality of the data distribution was tested using the Shapiro-Wilk test. The test revealed that the data distribution for several of the factors was not normally distributed, therefore, non-parametric statistical analysis methods have been employed. To conduct descriptive statistics we have reported Medians (Mdn) and Interquartile Range (IQR). To determine statistically significant differences between the users' engagement perceptions across the three systems, we have employed the Friedman test which is commonly used for within-subject design for data with three (or more) repeated outcomes where their distribution is not normal. The null hypothesis of the Friedman test is that the distribution is the same across the repeated measures (the three systems) [41]. For statistically significant differences between the measures, separate Wilcoxon signed-rank tests was conducted using Bonferroni adjustment, dividing the p value by the 3 tests, resulting to a new significance level (p) of 0.05/3=0.017.

The results of the individual factors of engagement were explored first, and are summarized in Table I and depicted in Fig. 7 for the web-based Dashboard system (*Dashboard*), the 2D DT (*2DDT*) and the VR DT (*VRDT*). The VRDT was particularly engaging in terms of Aesthetics (Mdn=6, IQR=2.5), Captivation (Mdn=5.5, IQR=2), and Challenge (Mdn=6, IQR=2.5), reflecting the ability of VR to deliver visually immersive and appealing graphics that absorb users and encourage reflection during data visualization tasks. The 2DDT also performed well in these areas, with high scores in Aesthetics (Mdn=5.5, IQR=1), Captivation (Mdn=5, IQR=1.5), and Challenge (Mdn=5, IQR=1). The Dashboard received the lowest scores for these factors, with Aesthetics (Mdn=4.5, IQR=1.5), Captivation (Mdn=3.5, IQR=2), and Challenge (Mdn=5, IQR=2), suggesting that the traditional dashboards are less engaging and cognitively stimulating than the DT approaches. However, Control was rated highest for the Dashboard (Mdn=6, IQR=1.5), likely due to users' familiarity with dashboard-based visualization systems and their ease of use. The 2DDT scored lower (Mdn=5.5, IQR=1.5), while the VRDT had the lowest score (Mdn=5, IQR=1), likely due to the complexity of navigating a virtual environment. Discovery (Mdn=5.5, IQR=2.5) and Exploration (Mdn=5.5, IQR=1) were rated high for the VRDT, and similarly for the 2DDT (Discovery: Mdn=5.5, IQR=1.5, Exploration: Mdn=5, IQR=1.5), suggesting that both systems supported spatial understanding and interactive exploration effectively. The Dashboard scored the lowest ratings for these factors (Discovery: Mdn=5, IQR=2; Exploration: Mdn=5, IQR=1.5). Creativity, Attention, and Interest were rated highest for the VRDT (Creativity: Mdn=4.5, IQR=3; Attention: Mdn=6, IQR=0.5; Interest: Mdn=5.5, IQR=2). The 2DDT was also perceived positively (Creativity: Mdn=4.5, IQR=3; Attention: Mdn=5.5, IQR=1; Interest: Mdn=5, IQR=2.5). The Dashboard received the lowest scores in these areas, with Creativity (Mdn=3.5, IQR=2), Attention (Mdn=5, IQR=1.5), and Interest (Mdn=5, IQR=2.5), indicating it was less engaging in these domains. Lastly, the VRTD received the highest scores in Novelty (Mdn=5, IQR=2.5) and Autotelism (Mdn=5.5, IQR=3.5), highlighting innovative and enjoyable user experiences. The 2DDT was also rated positively (Novelty: Mdn=5, IQR=2; Autotelism: Mdn=5, IQR=1), while the Dashboard was perceived as less engaging (Novelty: Mdn=4.5, IQR=3; Autotelism: Mdn=4, IQR=3), suggesting that this is due to the lack of innovative interactive features and enjoyment of the DT platforms.

The Overall Engagement score for the three conditions was then explored and the results are summarized in Table II and depicted in Fig. 8. Even though we are considering Median values due to the non-normal data distribution of our sample, we have also included the Mean results for a more clear understanding of the data. The VRDT mode received the highest engagement score out of the maximum 154 (Mdn=121, IQR=48), followed by the 2DDT (Mdn=113, IQR=23) and then the Dashboard (Mdn=98, IQR=24).

The Overall Engagement results were then further explored using the Friedman test of related samples to determine statistically significant differences between the users' perceptions of the three systems. The test revealed that the Overall Engagement scores (Table II) were not statistically significant (χ^2(2)=3.2, p=0.202), even though the VRDT scored quite higher (Mdn=121, IQR=48) than the Dashboard system in particular (Mdn=98, IQR=24), and also than the 2DDT (Mdn=113, IQR=23). The differences across systems for the individual engagement factors were also explored. There was

TABLE I
DESCRIPTIVE STATISTICS FOR THE DIFFERENT FACTORS AND SYSTEMS

Factor	System	Median	Min	Max	IQR
Aesthetics	Dashboard	5.5	1.5	7	1.5
	2D DT	5.5	3	7	1
	VR DT	6	2.5	7	2.5
Captivation	Dashboard	3.5	1	7	2
	2D DT	5	1	6	1.5
	VR DT	5.5	2	7	2
Challenge	Dashboard	5	3	7	2
	2D DT	5	1.5	7	1
	VR DT	6	2	7	2.5
Control	Dashboard	6	4	7	1.5
	2D DT	5.5	2	7	1.5
	VR DT	5	3	7	1
Discovery	Dashboard	5	1.5	7	2
	2D DT	5.5	3.5	7	1.5
	VR DT	5.5	3	7	2.5
Exploration	Dashboard	5	2.5	6	1.5
	2D DT	5	2	6.5	1.5
	VR DT	5.5	3	7	1
Creativity	Dashboard	3.5	1	5.5	2
	2D DT	4.5	1	6	3
	VR DT	4.5	2.5	7	3
Attention	Dashboard	5	3.5	6.5	1.5
	2D DT	5.5	3.5	7	1
	VR DT	6	3.5	7	0.5
Interest	Dashboard	5	2	7	2.5
	2D DT	5	2.5	7	2.5
	VR DT	5.5	2	7	2
Novelty	Dashboard	4.5	2.5	6.5	3
	2D DT	5	2	6.5	2
	VR DT	5	2.5	7	2.5
Autotelism	Dashboard	4	2	6	3
	2D DT	5	1	7	1
	VR DT	5.5	1	7	3.5

TABLE II
DESCRIPTIVE STATISTICS FOR OVERALL ENGAGEMENT

System	*Median*	*IQR*	*Mean*	*SD*	*Min*	*Max*
Dashboard	98	24	101.57	17.64	68.00	136
2D DT	113	23	107.30	20.04	60.00	138
VR DT	121	48	114.83	23.05	76.00	143

a statistically significant difference in Captivation between the three systems, (χ^2(2)=12.756, p=0.002) Post hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction with a significance level set at p $<$ 0.017, revealed statistically significant differences between the VRDT and the Dashboard (Z=-3.099, p= 0.002), and also with the 2DDT (Z=-3.002, p=0.003). Furthermore, there was also a statistically significant difference in Creativity between the three systems (χ^2(2)=15.537, p=<.001). Post hoc analysis (p $<$ 0.017) revealed a statistically significant difference for the VRDT with the Dashboard (Z=-3.276, p= 0.001), as well as between the 2DDT and the Dashboard (Z=-2.616, p= 0.009).

The results regarding the user experience were explored next and are presented in Table III. The VRDT was particularly positively rated for making users feel present in the environment (Mdn=7, IQR=2), for understanding the spatial layout of the environment (Mdn=6, IQR=2), the physical space (Mdn=7, IQR=3) and perceive distances effectively (Mdn=6,

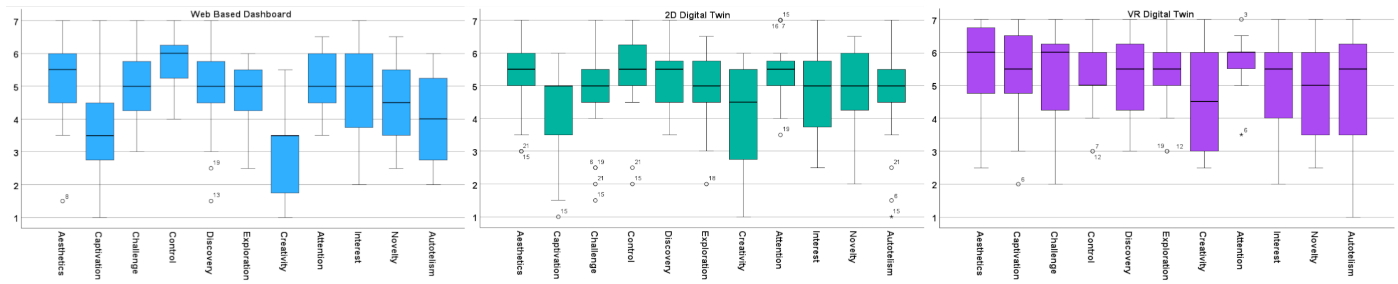

Fig. 7. Box-plots of each Engagement factor for the web-based Dashboard, the 2D, and VR DT.

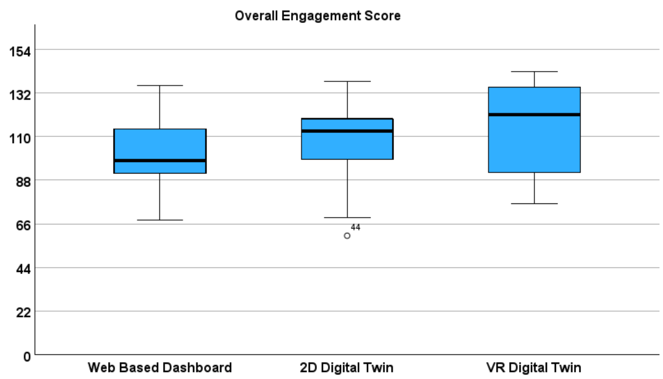

Fig. 8. Box-plots for Overall Engagement score for the three modalities.

IQR=2). However, the complexity in the use of the VRDT revealed challenges for some users, as reflected in lower scores for Task Completion (Mdn=5, IQR=3). The 2DDT was consistently perceived positively, particularly in spatial layout understanding (Mdn=6, IQR=2), the ability to observe changes in measurements and of conditions in the environment, demonstrating a good balance of graphical clarity and usability. The Dashboard was perceived highest in ease of task completion (Mdn=7, IQR=1), but was rated low on presence (Mdn=3, IQR=3) and spatial understanding (Mdn=3, IQR=5), revealing its limitations in immersive and interactive tasks. The overall data exploration experience was positively rated for all three systems, but in particular the 2DDT received the most consistent perceptions (Mdn=6, IQR=0)

At the end of the experience, the researchers conducted brief interviews to gather participants' impressions of the three systems. Many participants found the need to navigate and explore the environment in the VRDT to obtain specific measurements to be time-consuming, especially when accessing detailed information. However, the 3D representation in VR was positively rated for providing a strong sense of immersion and spatial understanding, especially because users were unfamiliar with the real environment. Several users noted that they preferred starting with the isometric view in VR, as it allowed them to quickly review data and select the area they wanted to explore. In contrast, the 2DDT was described as more structured, but it was less effective in conveying real-world spatial relationships. Some participants appreciated the 2DDT interface for its ability to clearly display changes in measured variables over time, which were facilitated by color-coded variations on the timeline. The Dashboard system on the other hand was perceived as the most efficient for completing tasks, with users highlighting their familiarity with such tools. While the dashboard and 2DDT were generally regarded as more intuitive and efficient for task completion, VR's isometric view improved ease of use; however, deeper exploration in VR was often seen as more time-consuming.

TABLE III
DESCRIPTIVE STATISTICS FOR USER EXPERIENCE QUESTIONS

Question	System	Mdn	Min	Max	IQR
I felt as if I was present in the environment.	Dashboard	3	1	7	3
	2D DT	5	2	7	2
	VR DT	7	2	7	2
I could understand the spatial layout of the environment.	Dashboard	3	1	7	5
	2D DT	6	4	7	2
	VR DT	6	2	7	2
I could perceive distances between sensor locations within the environment.	Dashboard	2	1	7	3
	2D DT	6	4	7	2
	VR DT	6	4	7	2
I gained a clear understanding of the physical space.	Dashboard	2	1	7	6
	2D DT	6	3	7	1
	VR DT	7	1	7	1
It was easy to understand condition changes over time across areas.	Dashboard	6	3	7	3
	2D DT	7	4	7	1
	VR DT	6	3	7	2
It was easy to complete the assigned tasks?	Dashboard	7	3	7	1
	2D DT	6	3	7	2
	VR DT	5	2	7	3
Rate your overall data exploration experience with this system	Dashboard	6	2	7	2
	2D DT	6	4	7	0
	VR DT	6	2	7	3

VI. DISCUSSION

The results of this study highlight the capabilities and potentials of DT systems in monitoring and interpreting IAQ. The findings demonstrate that DT technology both in 2D and VR are effective tools for real-time environmental data engagement, allowing users to analyze complex indoor conditions to make informed decisions; for example improving air quality that can mitigate health risks, reduce costs, and better manage resources.

In terms of the RQ1, the results demonstrate that user engagement varied between the three modalities. The VR DT was found to offer the highest levels of immersion, aesthetics, captivation, and interaction, offering novel and enjoyable experiences, suggesting that its immersive capabilities support increased engagement by allowing users to explore IAQ data in more interactive and intuitive ways. The 2D DT was also perceived very engaging, with participants appreciating its graphical clarity and structured interface supporting active data engagement. The Dashboard was found practical and familiar to users but was the least engaging. Even though users found it easy to complete the assigned tasks and effective for data retrieval, it lacked the immersive and exploratory features that made the DT systems more engaging.

To explore the extent to which the three modalities support users' ability to interpret environmental data efficiently and address RQ2, the results indicate that each system offers distinct advantages for data interpretation depending on the complexity of the task. The VRDT enabled users to discover patterns and trends interactively, supporting engagement and creative thinking, but with lower task completion efficiency. However, the need to navigate and explore the environment to obtain specific measurements was perceived as time consuming by some users. The 2DDT proved to be the most effective in supporting structured data analysis, particularly for identifying environmental trends over time, offering clear visual representations allowing users to quickly compare temperature, humidity, and air quality changes. In contrast, the Dashboard was the easiest to use but lacked the depth of exploration offered by the other two modalities.

In terms of the users' ability to develop spatial understanding of environmental conditions within the building (RQ3), this was mostly supported by the VRDT, which allowed users to navigate the environment freely and visualize IAQ variations in spatially contextualized ways through the technology's capability to provide an embodied sense of space. The 2DDT also supported strong spatial understanding but lacked immersion and free spatial movement, and was found less capable of conveying real-world spatial relationships than VR. The Web Dashboard scored the lowest in spatial understanding, with users reporting difficulty perceiving sensor distances and understanding the overall spatial layout, highlighting a fundamental limitation of traditional dashboards in representing spatial data intuitively.

Considering the results of this study, it can be argued that the ability of DTs to enable users immerse, visualise, understand the building and its spatial layout, track data patterns and analyze historical data, makes them as powerful tool for IAQ diagnostics and management. The study findings highlight the role of DTs as capable and effective decision-support systems for IAQ monitoring, supporting users to detect environmental risks, analyze trends, and develop their indoor air management strategies to optimize building performance, and promote healthier indoor environments.

VII. Conclusions, Limitations and Future Work

DTs can play a key role in public safety, particularly in hazardous indoor environments such as hospitals, schools, offices, and industrial facilities. The ability to provide real-time environmental insights through immersive interactive ways, can support ventilation management, detect pollutants, and assess air circulation effectiveness, helping to mitigate health risks associated with poor IAQ, airborne contaminants, and respiratory illnesses. The results of this study demonstrate the potential of DTs to support public safety and real-time environmental visualization and analysis, highlighting how their immersive and interactive affordances can support data understanding, detection, and management. The results also supports the notion that spatially contextualized data visualization through DT systems improves user engagement and data understanding, enabling better risk assessment and decision-making. This study also demonstrate the importance of intuitive system design and the affordances of each modality while validating the ability of DT technology to "bridge the gap" between expert and non-expert practitioners. Supporting decision-making without requiring extensive training or prior knowledge enable non-experts to provide critical insights into complex systems. Given that non-experts far outnumber experts, this could have a significant and positive impact on the daily management of buildings. The results of this study also align with the growing emphasis on creating user-friendly and accessible tools in the fields of human-computer interaction and user experience design.

However, this study has some limitations affecting the widespread generalisability of results. One limitation of the within-subject design is the potential for order effects, where participants may perform differently during each conditions due to increased familiarity with the task or reduced attention over time. To address this, we have issued tasks in random order and the systems were introduced sequentially, starting with the Dashboard, followed by the 2D, and then the VRDT, to minimize the "wow effect" of VR impacting earlier conditions. However, carryover effects related to exposure to an earlier system influences responses to subsequent systems remain a potential limitation. In order to mitigate this factor, we implemented a washout period between conditions, allowing participants to rest after each system use. The small sample size and the limited domain expertise of participants may also constrain the generalizability of findings. The sample has strong computer knowledge experience but relatively limited familiarity with VR and environmental data interpretation, reflecting a typical group of non-expert users and aligning with the study's aim to assess system engagement for general users. However, users with less computer experience may have different results. Lastly, the tasks performed during the experiments may differ from how users engage with systems in practice, and were designed to assess engagement based on real usage needs, but may not fully reflect the complexity of real world scenarios.

Future work will focus on conducting technical evaluation studies to assess the performance and scalability of the DT systems, and further expand their functionalities by incorporating additional sensors, readings, visualization methods and introduce new functionalities and interaction techniques. The research team also plans to integrate AI chatbot agent interactions, leveraging advancements in Large Language Models

(LLMs) to support user interaction and provide real-time data analysis and assistance to support decision-making. Additionally, future research will evaluate user motivation to adopt such technology, exploring perceptions of technology acceptance and usability.

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