The Juice Mixer: A Platform for Developing and Evaluating Immersive Analytics

Neven ElSayed*
Know Center Research GmbH.

Oliver Prentner†
Graz University of Technology.

Nicole Weidinger‡
Know Center Research GmbH.

Eduardo Veas§
Graz University of Technology, and Know Center Research GmbH.

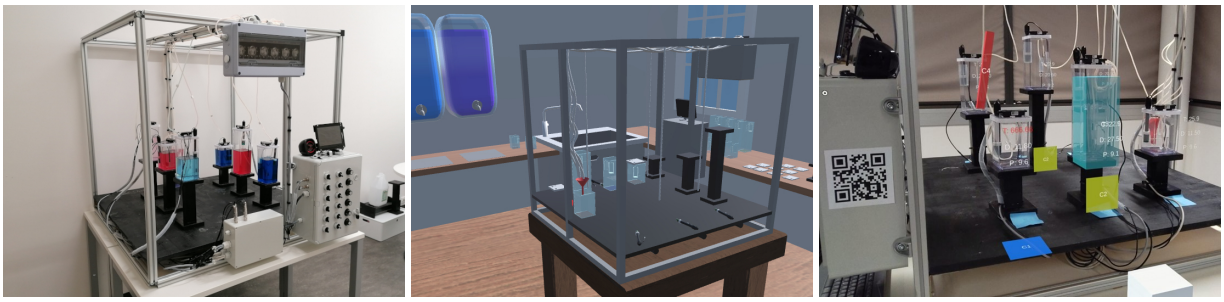


Figure 1: The JuiceMixer evaluation platform. From left to right: (a) the physical JuiceMixer installation, (b) the virtual reality version, and (c) the augmented reality version.

Abstract

This paper introduces *JuiceMixer*, a platform for immersive analytics (IA) development and evaluation. Designed as an industrial juice-mixing machine, it provides a familiar, task-oriented environment for immersive data interaction. The task conducted on the platform is intentionally simple and accessible, requiring no prior expertise. This design facilitates user studies focused on interaction and comprehension. JuiceMixer also enables the investigation of interaction fidelity, spatial embodiment, and collaborative performance across multiple immersive configurations (VR and AR). It integrates real-time sensing, remote access, and visualisation overlays to support controlled evaluation. The platform's architecture enables reproducible experimentation and supports systematic research on interface design, user adaptation, and collaborative decision-making.

Keywords: Immersive Analytics, Industrial Field, Augmented Reality, Virtual Reality, Mixed Reality, Evaluation, Digital Twin

1 Introduction

Immersive Analytics (IA) [17] has gained increasing interest for its potential to enhance data interaction and decision-making [5,11], particularly in industrial contexts. In this context, IA refers to both fully virtual Reality (VR) environments and Situated Analytics (SA) [6] using Augmented Reality (AR). Applications of IA now extend across training [12,28], operation and performance monitoring [15], maintenance [9], and the exploration of complex data across models [18]. These domains require tools that support both intuitive interaction and ongoing, practical evaluation.

Existing approaches to IA evaluation in industrial settings often fall into two categories. First, evaluations conducted on actual industrial machinery provide realistic insights but are limited by restricted access, operational risks, and the need for specialised expertise. Second, evaluations use abstract simulations with synthetic data that may fail to capture the complexity and contextual fidelity of real-world tasks. These limitations highlight the the challenge of conducting IA evaluations that balance realism, replicability, and are methodologically robust.

Moreover, meaningful evaluation of IA requires participant engagement with tasks that are both intuitive and contextually grounded. When domain-specific knowledge is absent, users may require extensive training, confounding the evaluation by introducing variability related to task familiarity rather than system design. This raises a critical challenge in distinguishing between user performance and system efficacy.

In response, this paper presents *Juice Mixer*, a simulated industrial machine designed as a flexible and accessible platform for developing and evaluating IA techniques. Designed in collaboration with industry partners and based on IA research, the platform enables controlled experimentation in a realistic and approachable setting. The juice-mixing task offers an intuitive metaphor for data manipulation, requiring no prior training while maintaining enough complexity to evaluate interaction, comprehension, and collaboration across VR and AR modalities.

Juice Mixer addresses logistical and methodological limitations in field-based IA studies by supporting reproducible experimentation, remote collaboration scenarios, and various visualisation and interaction strategies. This work aims to develop and validate a generalisable IA evaluation platform that supports collaborative, IA tasks in industrially inspired environments.

2 Background

IA is used to support data exploration, interpretation, and decision-making in complex domains. It employs VR and AR for data analysis, offering new forms of spatial interaction and embodied engagement [5]. Research in IA has grown in recent years, with applications ranging from network connectivity and graph analysis [3,27] to spatial data visualisation and 3D scatterplots [23].

In the context of AR, studies have explored meteorological data [19], collaborative exploration using hybrid displays [2], and spatially anchored overlays in real-world scenarios. The use of VR in IA remains more common than AR [16], likely due to limitations

*nelsayed@know-center.at
†oliver.prentner@tugraz.at
‡nweidinger@know-center.at
§eveas@tugraz.at

2025 IEEE Conference on Human Factors in Immersive Analytics (HFIA) | 979-8-3315-7827-5/25/$31.00 ©2025 IEEE | DOI: 10.1109/HFIA68651.2025.00005

979-8-3315-7827-5/25/$31.00 ©2025 IEEE
DOI 10.1109/HFIA68651.2025.00005

Authorized licensed use limited to: Technische Universitaet Graz. Downloaded on September 24,2026 at 15:32:13 UTC from IEEE Xplore. Restrictions apply.

of AR devices such as restricted field of view and limited spatial anchoring capabilities. SA is a related paradigm that emphasises the performance of analytic tasks within the spatial and contextual environment in which the data originate [6]. AR is often employed to support this approach by overlaying data visualisations onto physical systems [8]. Applications include museum scenarios with movable artefacts [1], accessibility mapping [10], and environmental monitoring [22]. VR has also been used in situated contexts to support architectural design evaluation [26], movement analysis in urban environments [13], and sports analytics [24, 25].

Digital twin (DT) technologies represent one of the most widely used forms of IA, particularly in industrial and operational settings [14, 20]. A digital twin typically consists of a physical system, its virtual counterpart, and a real-time data connection between them. These systems have been widely adopted for training, monitoring, and simulation across domains such as manufacturing, healthcare, and agriculture [4, 7]. When integrated with immersive interfaces, digital twins can enhance real-time visualisation, control, and scenario-based analysis [21].

Ongoing challenges in these DT systems include the need for naturalistic interaction, collaborative sensemaking, and reproducible user studies. Although existing systems demonstrate immersive potential, they often lack flexible platforms that support comparative evaluation across levels of embodiment, interface complexity, and collaborative conditions.

3 Juice Mixer Platform Design

To support systematic evaluation of IA techniques in industrial contexts, the *Juice Mixer* platform was developed based on a structured set of design requirements. These requirements reflect constraints observed in real-world environments, persistent methodological challenges, and feedback gathered through collaboration with industry partners. The goal is to create a configurable and reliable platform that simulates industrial workflows while enabling controlled experimentation with multiple user roles and analytic tasks. The requirements were defined with attention to human factors, enabling systematic evaluation of ergonomics, usability, cognitive load, and teamwork in IA.

Based in this goal, we organised the requirements into four principal categories: **Design Requirements**, addressing the physical, structural, and contextual characteristics of the platform; **Visualisation Requirements**, defining the perceptual and spatial features necessary for IA; **Interaction Requirements**, which cover input modalities, ergonomic setups, and task complexity; and **Data Requirements**, which specify the data models, integration protocols, and real-time behaviours required for realistic experimentation. Together, these categories form the foundation for evaluating IA systems in environments that are both experimentally robust and representative of industrial contexts.

3.1 Design Requirements

The Juice Mixer platform was developed to support the evaluation of IA techniques in realistic yet controlled industrial scenarios. It is intended to be accessible to participants without prior industrial experience and enables repeatable experimentation across a variety of task types. *The core design requirements are as follows*:

- Simulate an industrial environment using components of varying size and complexity, enabling tasks such as training, assembly, and maintenance across different levels of difficulty.
- Incorporate motorised and sensor-equipped elements that allow for task reconfiguration, physical interaction, and automation, while ensuring user safety and ergonomic accessibility.
- Use materials and lighting replicating industrial realism without introducing artefacts disrupting tracking systems.
- Provide a control unit and interface panel that conform to industry standards, featuring tangible inputs (e.g. toggles, dials, buttons) and a baseline feedback system (e.g. touchscreen and audio) for consistent evaluation conditions.
- Enable sensor data generation, real-time monitoring, cloud integration, and support for tracking infrastructure through structural mounts.

3.2 Visualisation Requirements

The Juice Mixer platform must support a range of visualisation scenarios that reflect challenges commonly encountered in IA environments. It is designed to enable systematic experimentation with spatial layout, data encoding, and perceptual complexity. *The key visualisation requirements are as follows*:

- Allow dynamic reconfiguration of physical elements (e.g. containers, placeholders) to evaluate the effects of spatial layout, including occlusion, visual density, and alignment accuracy.
- Provide multiple background surfaces and visual environments (e.g. transparent materials, animated physical components, and textures) to simulate AR-specific challenges such as spatial anchoring and visual interference.
- Integrate visual elements that represent embedded or semi-visible data sources, such as sensors concealed within physical components.
- Support visual variability through controllable parameters, including data frame rate, motor speed, colour intensity, and object movement, to facilitate the study of users' temporal perception and responsiveness to visual change.
- Include scenarios with occluded or hidden components (e.g. panels with doors) to encourage physical interaction, and off-screen elements to evaluate peripheral awareness, spatial memory, and contextual understanding in task performance.

3.3 Interaction Requirements

The platform must support a wide range of interaction modalities to enable diverse IA tasks. These modalities must reflect the variability of input methods used in industrial settings while remaining adaptable to different user roles, physical contexts, and ergonomic needs. *The key interaction requirements are as follows*:

- Support multiple input methods, including hand gestures, tangible object manipulation, touch interfaces, and controller-based input, to accommodate various user preferences and task types.
- Ergonomic positioning of interactive elements to ensure comfort during prolonged use, and to minimise fatigue across standing, seated, and collaborative configurations.
- Support for both discrete and continuous interaction types, allowing fine-grained control over parameters such as flow rate, mixing sequence, and system state.
- Configurable task complexity, enabling comparisons between new and expert users across tasks with differing cognitive and physical demands.
- Seamless transition between physical and virtual interactions, ensuring consistency in user expectations and system feedback across modalities.
- Enable robotic interaction with the platform to support remote analytics scenarios, in which a robot functions as a proxy operator within the physical environment.

3.4 Data Requirements

To support realistic, high-fidelity evaluation of IA techniques, the Juice Mixer platform must accommodate a range of data types and structures that reflect industrial usage. The system is intended to simulate the data dynamics of real-world processes while enabling analytical flexibility and experimental repeatability. *The key data requirements are as follows*:

- Support multiple data formats, including binary signals (e.g. on/off controls), discrete events (e.g. button presses), and continuous data streams (e.g. sensor outputs).

Authorized licensed use limited to: Technische Universitaet Graz. Downloaded on September 24,2026 at 15:32:13 UTC from IEEE Xplore. Restrictions apply.

- Allow multidimensional sensor data with interdependent variables, enabling the study of correlated behaviours.
- Provide real-time data streaming for immersive feedback and interaction, with consistent timing and minimal latency.
- Store historical data to support visual analysis tasks, including comparative exploration, trend detection, and time-based decision-making.
- Enable integration with digital twin platforms, simulation engines, and cloud-based systems to support remote access, persistent logging, and extended analytic capabilities.

Together, these four categories of requirements define a comprehensive design space for IA system evaluation in industrially inspired contexts. They are intended to support experimental control, usability, and reproducibility, while remaining adaptable to varied analytic tasks and interaction modalities. This structured foundation enables the development and assessment of immersive platforms that are technically reliable, cognitively appropriate, and representative of real-world industrial scenarios.

4 Hardware Architecture

The Juice Mixer system integrates a modular hardware architecture designed for reliability, real-time monitoring, and adaptive control (see Fig.1-a, Fig.2). This architecture provides a physical foundation for evaluating IA techniques by enabling sensor-driven interaction, automated feedback, and tightly coupled data visualisation. It supports experimentation with immersive interfaces that rely on real-time system state, tactile input, and fluid-based simulation of industrial workflows. The platform is structured around a distributed sensing and actuation framework, supported by a central processing unit and a lightweight communication protocol. Its modularity allows individual components such as pumps, containers, and sensors to be rearranged or substituted, enabling researchers to reproduce varied task environments while maintaining experimental control.

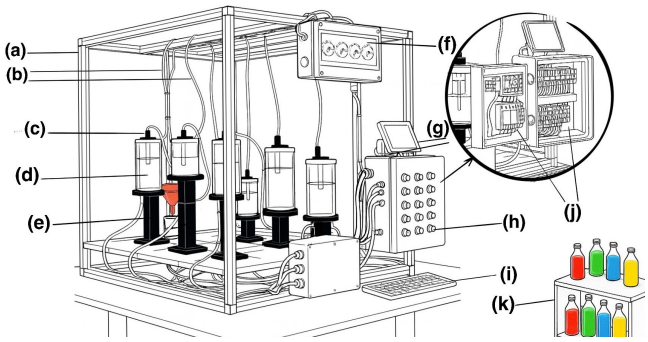


Figure 2: Juice Mixer system components: (a) Machine frame, (b) Flexible silicone tubing, (c) Sensors for real-time monitoring, (d) Transparent containers, (e) Movable container holders, (f) Motors behind transparent glass, (g) Display and speakers, (h) Control panel, (i) Keyboard and mouse, (j) Raspberry Pi unit, (k) Remote juice storage unit positioned away from the mixer body.

4.1 Sensor and Actuator Integration

The Juice Mixer system employs a suite of embedded sensors and actuators to enable real-time monitoring and control of physical processes. Core sensing components include waterproof temperature sensors, pH sensor modules, and waterproof ultrasonic sensors. These sensors provide continuous data on liquid temperature, acidity, and volume, respectively. The integration of these components supports precise, real-time feedback that is essential for dynamic system behaviour and data-driven IA scenarios.

Fluid control is achieved using 12V DC peristaltic pumps (Typ C), which operate in coordination with sensor input. These pumps provide directional flow and consistent dosing for fluid handling tasks. Structural elements, including 3 mm × 5 mm silicone tubing and cable mounting clips.

All sensors are installed without permanent adhesives. Each unit is mechanically secured using reversible fasteners or friction-fit mounts. This design allows for rapid removal, replacement, or repurposing of individual sensors, supporting experimental variation and re-use during assembly-oriented tasks. The overall integration of sensors and actuators enables researchers to replicate a range of industrial processes with high fidelity while maintaining ergonomic safety and operational flexibility.

4.2 Communication Layer

Sensor data within the Juice Mixer system is transmitted using the MQTT protocol. This protocol was chosen for its low overhead, lightweight architecture, and suitability for real-time communication in embedded systems. The MQTT broker is hosted on the system's Raspberry Pi and operates within a local Wi-Fi network. It enables efficient, asynchronous data exchange between components.

Sensor values are broadcast at fixed intervals to structured topics that support both aggregate and fine-grained access. This topic hierarchy provides flexibility for configuring experimental conditions and monitoring individual parameters during IA studies. This decoupled communication model supports system scalability, component interchangeability, and reliable data synchronisation in immersive and distributed task environments.

4.3 Control and Processing

At the core of the Juice Mixer system is a Raspberry Pi unit responsible for coordinating system behaviour. This device runs a lightweight Flask server that manages sensor polling, actuator control, and user interface delivery. The Raspberry Pi platform was chosen due to its affordability, flexibility, and suitability for embedded and networked applications. The control logic is implemented in Python, which enables integration of sensing, feedback, and interface operations. A dedicated background script listens to MQTT topics and forwards sensor data into an InfluxDB instance for real-time storage and retrieval. This setup facilitates adaptive system control while maintaining separation between low-level hardware tasks and higher-level analytic processes.

The architecture supports modular code deployment, allowing researchers to introduce new behaviours or adjust control parameters without altering the physical configuration. This flexibility enables the system to support a broad range of IA scenarios, including time-sensitive automation and reactive user guidance.

4.4 Data Handling and User Interaction

Sensor readings are persistently stored using InfluxDB 2.0, a time-series database optimised for structured temporal data. Sensor values are streamed into the database using a dedicated Python script that bridges the MQTT broker and the storage system. Data are recorded in a structured schema, allowing efficient filtering by sensor type and container name.

The InfluxDB instance is hosted locally on the Raspberry Pi and supports both web-based interaction and API-based access. This setup enables researchers to retrieve data for real-time analysis using standard interfaces. A Flask-based web application serves as the primary user interface. It presents live sensor values, system logs, and control functions through a browser-accessible dashboard. The interface can be accessed either via a directly connected touchscreen or remotely over the internal network.

The system supports scenarios in which remote users collaborate with or supervise the machine in real time. This allows researchers to investigate shared control, autonomy, and decision-making in IA settings where physical and virtual interactions are interwoven.

Authorized licensed use limited to: Technische Universitaet Graz. Downloaded on September 24,2026 at 15:32:13 UTC from IEEE Xplore. Restrictions apply.

5 JuiceMixer System Architecture

Building on the hardware and data infrastructure, the JuiceMixer platform includes a software architecture designed to coordinate sensory input, user interaction, and system logic in immersive environments. The system is structured using a Model-View-Controller (MVC) architecture, which facilitates modular design and controlled experimentation across different components (see Fig. 3).

The Model layer encodes core functionalities such as knowledge representation, task logic, user-driven recommendations, and behavioural detection. These elements are adaptable to suit different experimental protocols and user interaction scenarios. The View layer presents multimodal feedback through visual and haptic channels, supporting output across VR, AR, and robot-mediated interfaces. The Controller manages all interaction flow between the user and the system, coordinating direct input (e.g. gestures, tangible controls) and indirect input (e.g. remote or robotic agents).

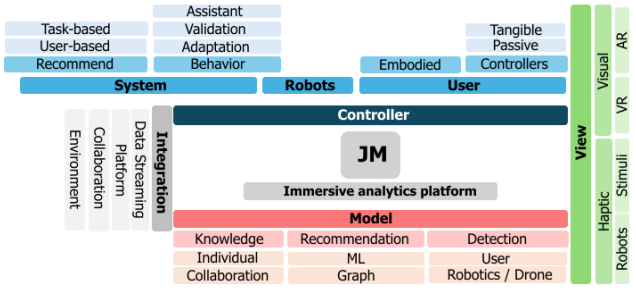


Figure 3: JuiceMixer platform architecture following the Model-View-Controller (MVC) design pattern.

This architecture allows researchers to adapt or substitute components of the platform without reconstruct the entire system. JuiceMixer serves as a flexible and efficient tool for prototyping and evaluating IA tasks. The modular structure enables iterative development and focused investigation of interface techniques, sensor configurations, and decision-making strategies. It also supports controlled variation in system autonomy, user input, and feedback complexity, which are central considerations in the study of IA.

6 Immersive Variants of JuiceMixer

To investigate IA across different levels of embodiment, spatial integration, and interaction fidelity, we developed two variants of the JuiceMixer platform: a VR implementation and an AR implementation. These immersive variants provide a controlled basis for analysing how embodiment and interface realism influence user performance, perception, and decision-making. Both variants are built on a shared data architecture and modular platform design, ensuring consistent behaviour across modalities and enabling repeatable evaluation of IA tasks in industrial-like settings. The platform is specifically designed to support research development and evaluation techniques, making it suitable for use in controlled studies, exploratory design, and iterative testing across embodied, non-embodied, and collaborative scenarios. Detailed guidance is provided on GitHub[1] to assist researchers in replicating the system and integrating it into diverse experimental workflows.

6.1 Virtual Reality Version

The VR implementation presents a fully simulated version of the JuiceMixer system (see Fig.1-b). All core components, including containers, pumps, control elements, and interface panels, are digitally represented within an immersive three-dimensional environment. This variant functions as a DT of the physical system, mirroring its structure and behaviour in real time.

[1] https://github.com/niciwei/JuiceMixer

Users interact with the environment through natural hand gestures and standard VR controllers, allowing multiple interaction techniques to be evaluated. These methods replicate the procedures of the physical platform while enabling greater flexibility in experimental control. The virtual environment is connected to the system's real-time data infrastructure, enabling live sensor values to be visualised in context. Historical data can also be retrieved within the virtual interface to support temporal analysis and training tasks.

This configuration removes physical constraints and allows for deployment in controlled experimental settings. It supports applications such as simulation-based instruction, remote task execution, and immersive visual analytics. The virtual variant is well suited to the evaluation of spatial reasoning, interaction techniques, and user performance in fully embodied virtual scenarios.

6.2 Augmented Reality Version

The AR implementation of the JuiceMixer enables interaction with the system in both embodied and non-embodied forms (see Fig.1-c). With the physical installation, AR provides situated visualisations of sensor data, historical performance panels, and overlays for adjusting parameters, retaining physical embodiment while enhancing interpretation through multimodal feedback. This configuration is suitable for investigating SA in controlled laboratory environments.

The same interface may also operate without the physical machine, where users interact with a spatially anchored virtual representation. In this mode, real-time or simulated sensor data remain accessible, and the physical machine can be controlled remotely via the API. This supports collaborative scenarios in which co-located users share the same virtual machine while communicating face to face, an option not available in VR, which places users in isolated environments. The AR version therefore facilitates shared presence and coordination in lightweight deployment contexts such as training, evaluation, and remote access.

7 Illustrative Use Case

The JuiceMixer platform can be used for IA studies across a wide range of scenarios. For example, participants with no prior expertise may be asked to prepare a batch of juice orders by deciding the sequence, allocating ingredients, and maintaining the target temperature by adding ice cubes. One participant operates the control panel with AR overlays, while a collaborator in VR monitors data and proposes adjustments. The task is accessible for participants to understand while encompassing the complexity of IA, including sequencing, resource management, and real-time monitoring. While this is one illustrative scenario, the platform is designed to support a broader range of experimental designs, enabling researchers to implement varied tasks for examining usability, workload, and collaboration in IA research.

8 Conclusion

This paper has presented JuiceMixer, a modular platform for investigating IA in industrial-like settings. By integrating a physical machine, real-time sensing, and immersive interfaces in VR and AR, the platform provides controlled conditions for evaluating interaction, visualisation, and collaboration strategies. It enables reproducible experimentation, supports both embodied and remote scenarios, and lowers the entry barrier for participants without prior expertise. JuiceMixer therefore contributes a scalable foundation for systematic study and iterative design in IA research.

Acknowledgments

This work is funded under the Austrian COMET Program, supported by the Federal Ministries of Transport, Innovation & Technology, Economy, Family & Youth, the State of Styria, and managed by the FFG.

Authorized licensed use limited to: Technische Universitaet Graz. Downloaded on September 24,2026 at 15:32:13 UTC from IEEE Xplore. Restrictions apply.

REFERENCES

[1] A. S. Calepso, P. Fleck, D. Schmalstieg, and M. Sedlmair. Exploring Augmented Reality for Situated Analytics with Many Movable Physical Referents. In *29th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–12. ACM, Christchurch New Zealand, Oct. 2023. doi: 10.1145/3611659.3615700 2

[2] M. Cavallo, M. Dolakia, M. Havlena, K. Ocheltree, and M. Podlaseck. Immersive Insights: A Hybrid Analytics System forCollaborative Exploratory Data Analysis. In *25th ACM Symposium on Virtual Reality Software and Technology*, pp. 1–12. ACM, Parramatta NSW Australia, Nov. 2019. doi: 10.1145/3359996.3364242 1

[3] M. Cordeil, T. Dwyer, K. Klein, B. Laha, K. Marriott, and B. H. Thomas. Immersive Collaborative Analysis of Network Connectivity: CAVE-style or Head-Mounted Display? *IEEE Transactions on Visualization and Computer Graphics*, 23(1):441–450, Jan. 2017. doi: 10.1109/TVCG.2016.2599107 1

[4] L. Damiani, M. Demartini, G. Guizzi, R. Revetria, and F. Tonelli. Augmented and virtual reality applications in industrial systems: A qualitative review towards the industry 4.0 era. *IFAC-PapersOnLine*, 51(11):624–630, 2018. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018. doi: 10.1016/j.ifacol.2018.08.388 2

[5] T. Dwyer, K. Marriott, T. Isenberg, K. Klein, N. Riche, F. Schreiber, W. Stuerzlinger, and B. H. Thomas. Immersive analytics: An introduction. In *Immersive analytics*, pp. 1–23. Springer, 2018. 1

[6] N. ElSayed, B. Thomas, K. Marriott, J. Piantadosi, and R. Smith. Situated analytics. In *2015 Big Data Visual Analytics (BDVA)*, pp. 1–8. IEEE, 2015. 1, 2

[7] M. Enders and N. Hoßbach. Dimensions of digital twin applications - a literature review. 08 2019. 2

[8] B. Ens, B. Bach, M. Cordeil, U. Engelke, M. Serrano, W. Willett, A. Prouzeau, C. Anthes, W. Büschel, C. Dunne, T. Dwyer, J. Grubert, J. H. Haga, N. Kirshenbaum, D. Kobayashi, T. Lin, M. Olaosebikan, F. Pointecker, D. Saffo, N. Saquib, D. Schmalstieg, D. A. Szafir, M. Whitlock, and Y. Yang. Grand Challenges in Immersive Analytics. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pp. 1–17. ACM, Yokohama Japan, May 2021. doi: 10.1145/3411764.3446866 2

[9] N. Gavish, T. Gutiérrez, S. Webel, J. Rodríguez, M. Peveri, U. Bockholt, and F. Tecchia. Evaluating virtual reality and augmented reality training for industrial maintenance and assembly tasks. *Interactive Learning Environments*, 23(6):778–798, 2015. 1

[10] R. Guarese, J. Becker, H. Fensterseifer, A. Calepso, M. Walter, C. Freitas, L. Nedel, and A. Maciel. A Usability Assessment Of Augmented Situated Visualization. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, pp. 636–637. IEEE, Atlanta, GA, USA, Mar. 2020. doi: 10.1109/VRW50115.2020.00169 2

[11] R. Hackathorn and T. Margolis. Immersive analytics: Building virtual data worlds for collaborative decision support. In *2016 Workshop on Immersive Analytics (IA)*, pp. 44–47. IEEE, 2016. 1

[12] C. Hoffmann, S. Büttner, and M. Prilla. Conveying procedural and descriptive knowledge with augmented reality. In *Proceedings of the 15th international conference on pervasive technologies related to assistive environments*, pp. 40–49, 2022. 1

[13] C. Hurter, N. H. Riche, S. M. Drucker, M. Cordeil, R. Alligier, and R. Vuillemot. FiberClay: Sculpting Three Dimensional Trajectories to Reveal Structural Insights. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):704–714, Jan. 2019. doi: 10.1109/TVCG.2018.2865191 2

[14] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks. Characterising the digital twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, 29:36–52, 2020. doi: 10.1016/j.cirpj.2020.02.002 2

[15] S. Kloiber, V. Settgast, C. Schinko, M. Weinzerl, J. Fritz, T. Schreck, and R. Preiner. Immersive analysis of user motion in vr applications. *The Visual Computer*, 36(10):1937–1949, 2020. 1

[16] M. Kraus, J. Fuchs, B. Sommer, K. Klein, U. Engelke, D. Keim, and F. Schreiber. Immersive Analytics with Abstract 3D Visualizations: A Survey. *Computer Graphics Forum*, 41(1):201–229, Feb. 2022. doi: 10.1111/cgf.14430 1

[17] K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas. *Immersive analytics*, vol. 11190. Springer, 2018. 1

[18] J. Moloney, B. Spehar, A. Globa, and R. Wang. The affordance of virtual reality to enable the sensory representation of multi-dimensional data for immersive analytics: from experience to insight. *Journal of Big Data*, 5(1):53, 2018. 1

[19] I. Ouedraogo, H. Nguyen, and P. Bourdot. Immersive analytics with augmented reality in meteorology: an exploratory study on ontology and linked data. *Virtual Reality*, 28(3):144, Aug. 2024. doi: 10.1007/s10055-024-01040-w 1

[20] J. Pirker, E. Loria, S. Safikhani, A. Künz, and S. Rosmann. Immersive virtual reality for virtual and digital twins: A literature review to identify state of the art and perspectives. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, pp. 114–115, 2022. doi: 10.1109/VRW55335.2022.00035 2

[21] N. Saporiti, F. Strozzi, and T. Rossi. Digital twin relationship with virtual reality and augmented reality: a bibliometric review. 01 2021. 2

[22] E. Veas, R. Grasset, I. Ferencik, T. Grünewald, and D. Schmalstieg. Mobile augmented reality for environmental monitoring. *Personal and Ubiquitous Computing*, 17(7):1515–1531, Oct. 2013. doi: 10.1007/s00779-012-0597-z 2

[23] J. A. Wagner Filho, M. F. Rey, C. M. D. S. Freitas, and L. Nedel. Immersive Visualization of Abstract Information: An Evaluation on Dimensionally-Reduced Data Scatterplots. In *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 483–490. IEEE, Reutlingen, Mar. 2018. doi: 10.1109/VR.2018.8447558 1

[24] N. Weidinger, N. El Sayed, G. Luzhnica, T. Schreck, and E. Veas. Immersive Analysis of Spatiotemporal Racing Data. In *Proceedings of the 2023 ACM Symposium on Spatial User Interaction*, pp. 1–12. ACM, Sydney NSW Australia, Oct. 2023. doi: 10.1145/3607822.3614542 2

[25] S. Ye, C. Zhu-Tian, X. Chu, Y. Wang, S. Fu, L. Shen, K. Zhou, and Y. Wu. ShuttleSpace: Exploring and Analyzing Movement Trajectory in Immersive Visualization. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):860–869, Feb. 2021. doi: 10.1109/TVCG.2020.3030392 2

[26] C. Zhang, W. Zeng, and L. Liu. UrbanVR: An immersive analytics system for context-aware urban design. *Computers & Graphics*, 99:128–138, Oct. 2021. doi: 10.1016/j.cag.2021.07.006 2

[27] D. Zielasko, B. Weyers, M. Bellgardt, S. Pick, A. Meibner, T. Vierjahn, and T. W. Kuhlen. Remain seated: towards fully-immersive desktop VR. In *2017 IEEE 3rd Workshop on Everyday Virtual Reality (WEVR)*, pp. 1–6. IEEE, Los Angeles, CA, USA, Mar. 2017. doi: 10.1109/WEVR.2017.7957707 1

[28] T. Zigart, F. Stürzl, D. Niedermayr, J. Wolfartsberger, and S. R. Sorko. Comparative evaluation of virtual reality and in-person onboarding for assembly trainings in manufacturing. In *2023 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*, pp. 167–174. IEEE, 2023. 1

Authorized licensed use limited to: Technische Universitaet Graz. Downloaded on September 24,2026 at 15:32:13 UTC from IEEE Xplore. Restrictions apply.