UNIVERSIDADE DE LISBOA
INSTITUTO SUPERIOR TÉCNICO

Immersive Analytics in Dam Safety Control

Nuno Filipe Verdelho Trindade

Supervisor : Doctor Alfredo Manuel dos Santos Ferreira Júnior
Co-Supervisors : Doctor Sérgio Bruno Martins de Oliveira
Doctor Daniel Jorge Viegas Gonçalves

Thesis approved in public session to obtain the PhD Degree in
Computer Science and Engineering

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Jury

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Funding Institution:
Fundação para a Ciência e a Tecnologia (2021.07266.BD)

2025

Abstract

Dam safety control consists of monitoring and analyzing observed data and comparing it with computed results from numerical models. Dam data visualization is typically carried out on desktop computers using traditional charts. Visual contextualization of the information contained in these charts with the area of the dam it pertains to is fundamental to understanding the overall behavior of dams. While nothing provides a more accurate spatial perception of the structures' features than standing in front of the actual dam, such a scenario is impractical. Dams are often located in remote locations, and data analysis is typically carried out in the office. And while looking at the data without contextualizing it with the dam is not ideal, looking at the real dam without contextualizing it with the data is equally problematic. Immersive analytics uses extended reality to generate immersive environments where data can be visualized. Our research explores how it can be applied to dam safety control to improve structural data visualization. We address a subarea called situated visualization, aimed at displaying information on-site contextualized with the object of analysis. However, because dam data analysis activities are typically carried out off-site, we focus on using virtual 3D models instead of the actual dam (proxsituated visualization). We address the development of specialized prototypes, which are used to support a user study designed to determine if and where proxsituated visualization can improve dam safety control. The study compares performance and user experience across multiple modes/devices (desktop computer, virtual reality, and augmented reality) with distinct levels of visual detail and data representation indirection. Our findings suggest that there are indeed some advantages in both user experience and analysis performance in immersive proxsituated environments, compared to traditional/non-immersive.

Resumo

O controlo da segurança de barragens consiste na monitorização e análise dos dados observados, comparando-os com resultados de modelos numéricos. A visualização de dados de barragens é normalmente realizada em computadores desktop, utilizando gráficos tradicionais. A contextualização visual da informação contida nesses gráficos com a zona da barragem a que se refere é fundamental para compreender o comportamento global das barragens. Embora nada proporcione uma perceção espacial tão precisa das características da estrutura como estar em frente à barragem real, tal cenário é pouco prático. As barragens estão frequentemente localizadas em locais remotos e a análise dos dados é geralmente realizada em gabinete. E embora olhar para os dados sem os contextualizar com a barragem não seja o ideal, olhar para a barragem real sem a contextualizar com os dados é igualmente problemático. A análise imersiva de dados aproveita a realidade estendida para gerar ambientes imersivos nos quais os dados podem ser visualizados. A nossa investigação explora como aquela pode ser aplicada ao controlo de segurança de barragens para melhorar a visualização de dados estruturais. Abordamos uma subárea denominada visualização situada, que tem como objetivo exibir informação in-situ contextualizada com o objeto de análise. Como a análise de dados de barragens é normalmente realizada fora do local, focamo-nos na utilização de modelos virtuais 3D em vez da barragem real (visualização proxsituada). Abordamos o desenvolvimento de protótipos, utilizados para apoiar um estudo com utilizadores, concebido para determinar se e onde a visualização proxsituada pode melhorar o controlo de segurança de barragens. O estudo compara o desempenho e a experiência de utilizador em vários modos/dispositivos (computador desktop, realidade virtual e realidade aumentada) com níveis distintos de detalhe visual e indireção na representação de dados. Os resultados sugerem certas vantagens na experiência de utilizador e desempenho da análise em ambientes

imersivos proxsituados em comparação com os ambientes tradicionais/não imersivos.

Keywords

ProxSituated Visualization

Situated Visualization

Immersive Analytics

Extended Reality

Dam Safety Control

Palavras Chave

Visualização *ProxSituada*

Visualização Situada

Análise Imersiva

Realidade Estendida

Controlo da Segurança de Barragens

Dedicated to my parents, Alice da Conceição Verdelho Borges and Albino José Trindade, whose love, sacrifices, and unshakable belief in me have made my achievements in life possible.

Acknowledgments

The completion of this PhD thesis would not have been possible without the guidance, support, and encouragement of many individuals and institutions, to whom I am deeply grateful.

First and foremost, I would like to express my sincere gratitude to my supervisors, Professor Alfredo Ferreira, Professor Sérgio Oliveira, and Professor Daniel Gonçalves, for their invaluable mentorship, insightful feedback, and support throughout this journey. Their expertise, patience, and encouragement have been fundamental to my growth as a researcher.

I am also grateful to Instituto Superior Técnico and to my hosting institutions, INESC-ID - Instituto de Engenharia de Sistemas e Computadores - Investigação e Desenvolvimento and LNEC - Laboratório Nacional de Engenharia Civil, for providing an excellent research environment and the resources necessary to carry out this work. A special acknowledgment goes to Professor João Madeiras Pereira from INESC-ID, whose guidance and support were instrumental in shaping my work.

I extend my appreciation to my supervisees at Instituto Superior Técnico for their enthusiasm, hard work, and inspiring collaborations. Working alongside them has been a rewarding experience that has enriched my academic journey.

I am profoundly thankful to my family, whose love and support have been my foundation. To my daughters, Francisca Verdelho Trindade and Catarina Verdelho Trindade, who bring joy and meaning to my life, thank you for your patience and for reminding me of what truly matters.

I would also like to express my gratitude to Fundação para a Ciência e a Tecnologia (FCT) for the financial support through the doctoral grant 2021.07266.BD, which made this research possible.

This work was supported by national funds through FCT, Fundação para a Ciência e a Tecnologia, under project UIDB/50021/2020 (DOI:10.54499/UIDB/50021/2020) and performed under the auspices of UNESCO Chair on AI & VR at the University of Lisboa.

Contents

List of Figures

List of Tables

Acronyms

2D Two-dimensional.

3D Three-dimensional.

AEC Architecture, Engineering and Construction.

AR Augmented Reality.

BIM Building Information Modeling.

CAD Computer-aided Design.

CDD Concrete Dams Department.

FCT *Fundação para a Ciência e a Tecnologia*.

FEM Finite Element Method.

GIS Geographic Information System.

GNSS Global Navigation Satellite System.

GOLP Group of Lasers and Plasmas.

HDHI High Visual Detail and High Spatial Data Indirection.

HDLI High Visual Detail and Low Spatial Data Indirection.

HDRP High Definition Render Pipeline.

HMD Head-mounted Display.

INESC-ID *Instituto de Engenharia de Sistemas e Computadores - Investigação e Desenvolvimento*.

IST *Instituto Superior Técnico*.

LDHI Low Visual Detail and High Spatial Data Indirection.

LDLI Low Visual Detail and Low Spatial Data Indirection.

LiDAR Light Detection and Ranging.

LNEC *Laboratório Nacional de Engenharia Civil*.

LOD Level of Detail.

MR Mixed Reality.

MSc Master of Science.

PC Personal Computer.

PhD Doctorate of Philosophy.

R&D Research and Development.

SDK Software Development Kit.

SHM Structural Health Monitoring.

SUS System Usability Scale.

UAV Unmanned Aerial Vehicle.

UCLA University of California, Los Angeles.

UI User Interface.

UL University of Lisbon.

VR Virtual Reality.

XR Extended Reality.

Chapter 1

Introduction

The analysis of data concerning physical phenomena is a necessity across the distinct domains of engineering. It's through the exploration of such data that engineers can understand and gain insights into the studied phenomena. Only by addressing those insights can data be made actionable in the real world. The resulting actions can consist *e.g.,* of interventions in design, optimization, failure prevention, or risk mitigation, among many others.

Data visualization plays a key role in that analysis process. While the area of information visualization (*InfoVis*) typically tackles abstract data, like stock market trends, scientific visualization (*SciVis*) is directed at tangible, physical data [134] generally found in engineering processes.

As such, *SciVis* commonly focuses on spatial data, frequently time-dependent, generated by scientific processes [56], namely from dynamic physical phenomena. While Three-dimensional (3D) in nature, this data is frequently represented and analyzed using Two-dimensional (2D) visual idioms/plots.

The common rationale for opting for 2D data representations is: 'everyone knows that 3D charts are bad and hard to read' [2]. Indeed, for certain application contexts (sometimes even those inherently 3D), that appears to be the case [25], [68]. Nonetheless, often, this perception arises from using 3D in scenarios where it is ineffective and detrimental in providing meaningful insights. A typical example is using 3D charts to represent lower-dimensional data, simply due to their visual appeal [115].

However, there are specific contexts, where 3D *SciVis* can in fact make sense [36], [141]. Such happens typically when the data is so intimately interconnected with the spatial features [64] of physical referents (the real-world tangible objects being analyzed) that it has to be seen in its spatial context to be properly understood [156]. An example is visualizing structural data associated with engineering structures, like buildings or dams.

While the spatial context brought by 3D representations can be advantageous, its full potential is hardly achieved if the proper devices and visualization environments are not used. Unlike desktop systems with conventional 2D screens, Extended Reality (XR) technology can offer a truly immersive experience. This immersive XR experience has been shown to increase 3D spatial perception, which can potentially enhance the analysis of 3D representations [66], [79], [121]. XR is also typically associated with a higher sense of presence, engagement, and motivation [81], [92], [97], [174]. As such, there has been an increased research interest in applying innovative immersive technologies to *SciVis* [99].

This growing significance of effective visualization and analysis through the use of immersive technologies has resulted in the emergence of new fields. One promising field is 'immersive analytics', which aims to enhance analytical interpretation and decision-making [148], namely through the use of XR technologies. Immersive analytics can be described as the analysis of data using immersive technologies. These technologies can promote the user's immersion in virtual environments or augment their view of the real world by overlaying relevant graphical elements.

Immersive analytics also aims to enhance user embodiment in the framework of data analysis. With that objective, user-friendly natural user interfaces are preferred. Natural interfaces allow interaction through actions grounded in real-world, everyday human behavior [126]. In that sense, immersive analytics is an interdisciplinary field that bridges human-computer interaction with data visualization/analysis [37].

A characteristic of immersive analytics is the possibility of analyzing data contextualized with the object of analysis. This characteristic has been framed as a subdomain of immersive analytics, generally designated by 'situated analytics'. An example of such a concept is the superimposition of thermal performance data directly on the walls of a building, thus contextualizing the thermal characteristics with specific facade features.

In that scope, Satriadi *et al.* [138] proposed an extended model of situated visualization by considering two scenarios based on the relation between users and the object of analysis: *proxied situated* visualization (also designated *proxsituated*) and *immediate situated* visualization. The first can be associated with technologies like Virtual Reality (VR) or Augmented Reality (AR) and enables data visualization over a proxied representation of the physical object being analyzed (the 'physical referent') and the surrounding environment. The second typically uses AR to represent data directly over the real/immediate physical referent.

The two situatedness [57] modalities are often applied to increase analysis contextualization, which is especially important in cases where the physicality of the referent is fundamentally relevant. However, they are typically directed at distinct scenarios. *immediate situated* visualization is mainly directed at *on-site* scenarios, where users are in the near proximity of the physical referent. *proxsituated* visualization is generally aimed at *off-site* scenarios, where the physical referent is located at a remote distance from users.

1.1 Motivation

Dam safety control is a complex activity that consists of monitoring and analyzing observed data and comparing it with computed results from numerical models. In the scope of the safety control analysis tasks, dam data visualization is typically carried out by dam engineers and technicians on desktop computers, using traditional charts. Visual contextualization of the information pertained in these charts with the area of the dam being analyzed is not always straightforward. However, in a domain such as dam safety control, where critical safety data is so intimately related to its physical referent characteristics, contextualization is key.

While nothing provides a more accurate spatial awareness of the structures' features than standing in front of the actual dam, such a scenario is frequently impractical. Dams are often located in remote locations, and dam data analysis is typically carried out off-site, in the office, and not in the field. Regardless, one could argue that, while looking at the data without contextualizing it with the dam is not ideal, looking at the real dam without contextualizing it with the data is equally problematic in an analysis scenario.

We believe that the application of immersive *proxsituated* visualization methods to dam safety control may offer an ideal opportunity for overcoming the aforementioned contextualization difficulties. These methods have the potential to enable analytics environments where users can interact in a natural way with realistic models of dam structures. Such environments may be the answer for an effective contextualization of the data with a reliable depiction of the object of analysis.

1.2 Thesis Statement

This research explores how immersive analytics concepts can be applied to dam safety control to improve structural data visualization performance. With that objective, we address the subarea of immersive analytics called situated visualization, which is aimed at displaying information contextualized with the object of analysis. However, because dam data analysis activities are typically carried out *off-site*, we focus on using virtual 3D models instead of the actual object of analysis (*proxsituated* visualization).

We develop a user study to determine if and where *proxsituated* immersive visualization can improve dam safety control. With that objective, we address the development of specialized prototypes, aimed at supporting the user study, which apply *proxsituated* environments to dam structural data analysis.

We aim to compare the performance and user experience across multiple devices and modalities (desktop computer, virtual reality, and augmented reality) with distinct referent visual detail levels and various degrees of data representation spatial indirection [178].

Therefore, the thesis statement of this dissertation can be expressed as follows:

> **Immersive *proxsituated* visualization can be used to effectively contextualize structural data with the physical structure of dams, resulting in increased analytics performance and user experience.**

In the scope of the above thesis statement, the research questions for this dissertation can be defined as follows:

RQ1 *Are there any improvements in performance or user-experience in dam structural data analysis when using immersive proxsituated environments, in comparison with conventional desktop environments?*

RQ2 *Are there any substantial differences in performance or user-experience in dam structural data analysis when using augmented reality proxsituated environments in comparison with virtual reality proxsituated environments?*

RQ3 *Is dam structural data analysis performance or user experience in proxsituated environments influenced by the visual detail of the physical referent representation?*

RQ4 *Is dam structural data analysis performance or user-experience in proxsituated environments influenced by the level of spatial indirection of the data representation?*

1.3 General Methodology

To evaluate the thesis, we followed a research methodology that included an exploratory stage, experimental evaluation, and empirical analysis. The exploratory stage was conducted to determine the feasibility of using XR technologies in the dam safety control domain. It served both as a formative research step and a design probe before formal hypothesis testing. It included the development of a series of relevant prototypes, which helped establish the foundational insights that shaped the experimental design.

As we will address further ahead, the exploratory stage helped us assess the potential of proxsituated analytics in the actual engineering domain. In particular, on how immersive technologies could be used to represent structural dam data in context. Likewise, it enabled us to identify key variables related to visualization and interaction. Furthermore, this stage fostered the engagement with real users and technical constraints early on, through a process of experimentation with alternative approaches to situated visualization.

A controlled user study was then designed to empirically evaluate the effects of immersive proxsituated visualization on dam structural analysis. This study was grounded on the research questions proposed in Section 1.2, which collectively operationalize the thesis statement.

Within the scope of RQ1, we wanted to evaluate the foundational premise of the thesis by comparing immersive proxsituated environments against conventional desktop-based tools. If indeed differences existed, namely enhancements in performance and user experience, measurable improvements would be observed. With that objective, we established a baseline condition (Personal Computer (PC) desktop application) and compared it against spatially rich, embodied immersive environments (VR and AR) for the same relevant set of analysis tasks.

In the context of RQ2, we wanted to measure the role of modality within immersive environments. In particular, we sought to determine whether AR and VR offer distinct levels of benefit in data analysis. Within that scope, we aimed to identify which immersive mode contributes more substantially to the potential improvements. We included both AR and VR also to examine how the nature of the immersive experience (complete immersion *versus* the preservation of the real-world surrounding context) influenced the results. With that objective, we compared the performance and user experience in both modes using the same models, interaction schemes, and data configurations, for the same relevant analysis tasks. This comparison allowed the evaluation of differential effects between approaches.

Within the scope of RQ3, we aimed to probe a critical design variable underpinning analytics performance within immersive environments, which we identified during the exploratory stage: the visual detail of the physical referent representation. We wanted to understand if analyzing data within a visually more faithful referent would influence performance. To test this condition, we addressed two levels of visual detail for the referent representations: *flat shaded* surfaces (corresponding to lower detail) and the use of surfaces with photographic textures (corresponding to higher detail). We tested these two variations for the same relevant analysis tasks.

Within the context of RQ4, we aimed to investigate how the spatial relationship between data and referent (a relevant variable identified during the exploratory stage) affects the performance of structural data analysis. In particular, we wanted to know if a lower level of spatial indirection, where data is embedded in the referent, corresponds to a better performance than a higher level of spatial indirection, where data is represented at a certain distance from the referent representation. To evaluate these two variations, we tested how users would perform the same relevant analysis tasks when data was represented directly over the dam structure and in floating panels.

To also measure the combined effect of visual detail and spatial indirection, we devised a series of variants that translate the multiple combinations between these two variables and for each of the visualization modalities (PC, VR and AR). These were tested for the same set of relevant analysis tasks. The aim was to understand *e.g.,* if the combined effect of higher visual detail and lower indirection resulted in better or worse performance than lower visual detail and higher indirection.

To evaluate user performance across different visualization conditions, we measured metrics such as task completion time and success rate. To assess user experience, we considered multiple factors, including usability, engagement, and perceived usefulness, which are described in detail in Section 6.1.

1.4 Contributions

The research work carried out in this thesis led to the following scientific contributions:

- A set of **assessments** of the performance and user experience of distinct *proxsituated* visualization modes in dam structural data analysis. We compared the efficiency of dam analysis environments using XR and desktop PCs. We also analyzed the differences between augmented and virtual reality in that scope. Furthermore, we compared two configurations with distinct levels of visual detail of the physical referent representation. We also compared two configurations with distinct levels of spatial indirection of the data visual representation. Likewise, we assessed the differences between four distinct variants resulting from the combination of distinct levels of both visual detail and data spatial indirection.

- A collection of **guidelines** for developing situated extended reality tools for dam safety control. These guidelines are individualized in five consecutive stages: conceptualization, design, implementation, testing & evaluation, and integration. In addition, a general costs-benefits discussion is also carried out.

- A **framework** for XR *proxsituated* dam safety control application development. This framework was built for abstracting relevant processes of application implementation such as interaction in the virtual environment, dam-related physical phenomena representation, structural data representation and data management.

The scientific output produced during the Doctorate of Philosophy (PhD) work includes eight articles published in scientific journals, conferences, and book chapters. Two of these articles were published in *Scimago* 'Q1-rated' journals at the time of this writing (in *Automation in Construction* and *IEEE Transactions in Learning Technologies*). It also includes three posters presented at conferences and other events. One of the posters earned the distinction 'Best Poster Award'. While some of the work produced falls outside the scope of dam safety control, it directly addresses the use of immersive visualization.

1.4.1 Journals

We have published four articles in scientific journals. The articles concern different aspects of immersive visualization. One of the articles is a systematic literature review on applying extended reality to the Architecture, Engineering and Construction (AEC) area. Two of the articles address the use of immersive analytics in dam safety control.

- [161] Nuno Verdelho Trindade, Alfredo Ferreira, João Madeiras Pereira, and Sérgio Oliveira. Extended reality in AEC. Automation in Construction, Volume 154, October 2023, 105018, DOI: 10.1016/j.autcon.2023.105018

- [159] Nuno Verdelho Trindade, Lídia Custódio, Alfredo Ferreira, and João Madeiras Pereira. Improving Ray Tracing Understanding With Immersive Environments, in IEEE Transactions on Learning Technologies, vol. 17, pp. 1975-1988, 2024, DOI: 10.1109/TLT.2024.3436656

- [162] Nuno Verdelho Trindade, Alfredo Ferreira, and Sérgio Oliveira. DamAR: Augmented Reality in Dam Safety Control. International Journal on Hydropower and Dams, no. 5 vol. 25, p. 56-62, Aqua Media International Ltd., Wallington, England, 2019, https://www.hydropower-dams.com/articles/damar-augmented-reality-in-dam-safety-control/

- [165] Nuno Verdelho Trindade, Pedro Leitão, Daniel Gonçalves, Sérgio Oliveira, and Alfredo Ferreira. The Role of Situatedness in Immersive Dam Visualization: Comparing Proxied with Immediate Approaches. Computers 2024, 13, 35, DOI: 10.3390/computers13020035

1.4.2 Conferences

We have published three articles and presented them at international conferences. The three articles concern different aspects of immersive visualization. Two of the articles address the use of immersive analytics in dam safety control:

- [164] Nuno Verdelho Trindade, Pedro Leitão, Daniel Gonçalves, Sérgio Oliveira, and Alfredo Ferreira. Immersive Situated Analysis of Dams' Behavior. 5th International Conference on Graphics and Interaction - ICGI 2023, p. 105-112, Eurographics, IEEE, Tomar, Portugal, 2023, DOI: 10.1109/ICGI60907.2023.10452725

- [163] Nuno Verdelho Trindade, Alfredo Ferreira, and Sergio Oliveira. Extended reality in the safety control of dams. 4th International Dam World Conference, vol. 1, p. 71-89, LNEC, Lisbon, Portugal, 2020, https://repositorio.lnec.pt/jspui/handle/123456789/1012969

- [158] Nuno Verdelho Trindade, Óscar Amaro, David Brás, Daniel Gonçalves, João Madeiras Pereira, and Alfredo Ferreira. Visualizing Plasma Physics Simulations in Immersive Environments. In Proceedings of the 19th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - IVAPP; ISBN 978-989-758-679-8; ISSN 2184-4321, SciTePress, pages 645-652, Rome, Italy, DOI: 10.5220/0012357100003660

1.4.3 Book chapter

We produced a book chapter, which addresses the use of immersive analytics in Structural Health Monitoring (SHM), including SHM in dam safety control:

- [160] Nuno Verdelho Trindade, Alfredo Ferreira, Daniel Gonçalves, and Sérgio Oliveira. The future of structural health monitoring with extended reality (Chapter 30). In Woodhead Publishing Series in Civil and Structural Engineering, Digital Transformation in the Construction Industry, Woodhead Publishing; ISBN 9780443298615; Elsevier, Woodhead Publishing, pages 593-620. DOI: 10.1016/B978-0-443-29861-5.00030-5

1.4.4 Posters

We produced a total of three posters in international conferences and in one national event for PhD students:

- Pedro Leitão, Nuno Verdelho Trindade, Sérgio Oliveira, and Alfredo Ferreira. Dam Health Monitoring with VR. 4th International Conference on Graphics and Interaction - ICGI 2022, Eurographics, IEEE, Aveiro, Portugal, 2022, https://gpcg.pt/icgi2022/

- Nuno Verdelho Trindade, Alfredo Ferreira, Sérgio Oliveira, and Daniel Gonçalves. Situated Immersive Analytics in Dam Safety Control. PhD DEI 2023, Departamento de Engenharia Informárica, Instituto Superior Técnico, Lisboa, Portugal, 2023, https://dei.tecnico.ulisboa.pt/en/news/campus-community/the-phd-dei-2023-was-a-success

- (**Best Poster Award**) Nuno Verdelho Trindade, Óscar Amaro, David Brás, Daniel Gonçalves, João Madeiras Pereira, and Alfredo Ferreira. Visualizing Plasma Physics Simulations in Immersive Environments. 19th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - IVAPP, Rome, Italy, https://visigrapp.scitevents.org/PreviousAwards.aspx#2024

1.5 Context

This dissertation falls within the domains of human-computer interaction and scientific visualization (of a physical entity - dams - and phenomena - structural behavior/data). It focuses on using XR to enable immersive analytics and visualization. In particular, it addresses situated analytics, namely *proxsituated* visualization[1].

It tackles the application of *proxsituated* visualization to civil engineering. It focuses on a major discipline of civil engineering, which is dam engineering. In particular, it covers a domain of dam engineering called dam safety control. In detail, it delves into a transversal area called SHM in the scope of the analysis of dam structural data.

This work was primarily developed as a PhD student at *Instituto Superior Técnico* (IST), University of Lisbon (UL). It was also developed within two host institutions: *Instituto de Engenharia de Sistemas e Computadores - Investigação e Desenvolvimento* (INESC-ID) and *Laboratório Nacional de Engenharia Civil* (LNEC).

At INESC-ID I was first attributed the role of *Trainee* and later integrated as an *Early Stage Researcher* with the Graphics and Interaction scientific area. At LNEC I was attributed the role of *Fellow* ('*Bolseiro*') of the Concrete Dams Department (CDD). The doctoral work was supported by a PhD grant with *Fundação para a Ciência e a Tecnologia* (FCT) (2021.07266.BD).

INESC-ID is a Portuguese private, non-profit Research and Development (R&D) institution in the area of Computer Science and Electrical and Computer Engineering. It was founded in 1999 and has been an Associate Laboratory of the Portuguese Ministry of Sci-

[1] A more detailed version of the title of this dissertation, incorporating terminology suggested by members of the Committee, would be: 'Immersive ProxSituated Analytics Performance and User Experience in Dam Safety Control'. The original title remains unchanged due to administrative constraints.

ence, Technology and Higher Education since 2004[2]. It includes 10 scientific areas, nearly 200 researchers, 200 students, and more than 50 research, technical and support staff members.

The Graphics and Interaction scientific area at INESC-ID is dedicated, within computer science, to computer graphics, human-computer interaction, and behavioral and social sciences. Its research scope includes deep graphics, medical interfaces, information visualization, education gamification, accessibility, and social inclusion.

This work was developed in close proximity with domain experts from the CDD at LNEC, where user studies were also carried out. LNEC is a Portuguese research and development institution whose mission includes promoting scientific research, technological development, and the definition of good practices in the Civil Engineering field. LNEC often assists the Government in the development of public policies regarding different sectors of Public Administration[3]. The CDD has existed since 1961 and is one of the eight departments of LNEC. The CDD is formed by three central units: Applied Geodesy, Monitoring/Observation and Modeling and Rock Mechanics.

In addition to extensive collaboration with INESC-ID and LNEC, during the completion of this doctoral work, there was also cooperation with the Group of Lasers and Plasmas (GOLP) at IST, in particular in exploratory activities related to immersive environments.

A collaboration with the University of California, Los Angeles (UCLA)s Physics and Astronomy Department is also presently being carried out in the scope of the development of additional functionalities for the above-mentioned immersive data analysis environment that we had previously created. This work is peripheral to our thesis theme, as it is not related to the safety control of dams.

1.6 Document Outline

This document is organized into eight chapters. Apart from the introduction (Chapter 1), we start by explaining, in Chapter 2, the fundamental concepts needed for supporting the different aspects addressed in the rest of the document. Computer science concepts pertaining to XR, immersive analytics, and situated analytics are addressed. Fundamental civil engineering concepts concerning dam safety control are also explained.

Chapter 3 describes and discusses previous research work related to the main objectives of the thesis. Scientific work concerning XR in AEC, immersive visualization in dam engineering, situated analytics, and *proxsituated* analytics is addressed.

In Chapter 4, we describe the exploratory process carried out during the development

[2]About INESC-ID: https://www.inesc-id.pt/about-us/

[3]LNEC's mission: https://www.lnec.pt/en/lnec/presentation/mission/

of this dissertation work. In that scope, we address a series of aspects related to situated analytics in dam safety control.

Chapter 5 discusses the characteristics, conceptualization, and challenges of developing '*DamXR*', a framework for abstracting the implementation of *proxsituated* dam safety control applications.

Chapter 6 describes the development of a user study. This study aims to answer the research questions and is supported by a prototype developed with the framework described in the previous chapter. We present the methodology, results, discussion, and limitations of the study.

In Chapter 7, we describe a set of guidelines for supporting the development of immersive situated applications for dam safety control.

Finally, in Chapter 8, we present the conclusions of the thesis. We discuss the main results of the research work previously described. We also address possible directions for future work concerning the use of immersive, *proxsituated* visualization in dam safety control.

Chapter 2

Background

This chapter addresses relevant background concepts needed to support the themes explored in this thesis. The first of this set of concepts is extended reality (XR), a group of technologies aimed at modifying how users experience reality. The second is immersive analytics, an emerging visualization field that uses XR in data analysis. The third background concept is a subarea of immersive analytics designated by situated analytics/visualization, which focuses on framing data within the physical object or context being analyzed. The chapter also covers fundamental concepts of dam safety control, which is the domain of civil engineering that the thesis focuses on.

2.1 Extended Reality

The term XR refers to the use of real and virtual combined environments generated by computer technology. Common examples of XR are VR and AR, whose popularity has been growing in the last decades. Milgram and Kishino [110] conceptualized the XR spectrum using a construct that they named the 'reality–virtuality continuum' [160]. This continuum is limited by real-world environments at one extreme and exclusively virtual environments at the other (Figure 2.1).

VR is purely digital. It allows users to become fully immersed in digital environments and be transported to alternative realities. Real environments are at the opposite end, as they are entirely physical. What lies between the real and the entirely virtual is referred to as Mixed Reality (MR). In MR, the real and the digital co-exist within a shared space [160].

Moreover, in its typical application context in the real world, MRs closer to the real environment tends to be used *on-site*. An example is AR, which allows the augmentation of the real world through the overlay of virtual elements. Conversely, MRs closer to the digital, are more likely employed *off-site*, as illustrated in Figure 2.1. An example is aug-

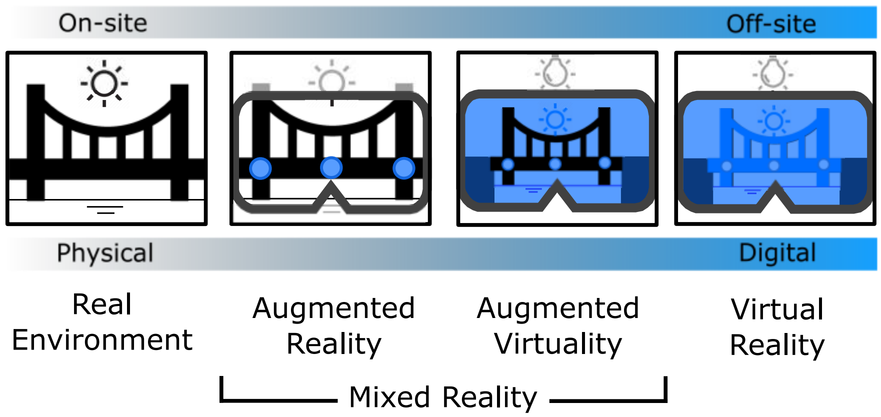


Figure 2.1: A representation of Milgram and Kishino's reality–virtuality continuum [110], which scopes the spectrum of real and virtual combined environments generated by computer technology. The mapping of the spectrum with physicality (from physical to digital) and the application context (from *on-site* to *off-site*) is also represented [160].

mented virtuality, where virtual environments are supplemented by the projection of real elements [160].

XR can be enabled in a wide range of visualization devices. General-purpose 2D screen-based touch devices, like smartphones or tablets, are a widespread option for supporting *on-site*-oriented AR (Figure 2.2, left). Users can point the device to the object they want to augment and visualize the superimposition of relevant virtual elements to that object [160].

For maximizing the immersion of users in purely virtual environments, VR Head-mounted Displays (HMDs)/headsets are becoming the norm (Figure 2.2, right). These devices are typically equipped with gyroscopes, accelerometers, and depth cameras, which allow them to track the position and orientation of the user's head (and other body parts, like the hands) within a three-dimensional space [160]. This process, commonly known as 'tracking', enables the real-world position and orientation of the user body to be accurately reproduced within the virtual environment [160].

AR HMDs like *Microsoft's HoloLens* provide a hands-free way of augmenting reality by overlaying digital holograms onto the physical environment. And more recent XR HMDs, like *Meta's Meta Quest 3* (Figure 6.1, right) support both AR and VR modes [160].

Note: The topics discussed in this section were addressed by Verdelho Trindade *et al.* [160].

Figure 2.2: AR-enabled *on-site* visualization of data overlaid in dams using a tablet (left) and off-site VR-enabled dam data visualization using an VR HMD (right) [160].

2.2 Immersive Analytics

Immersive analytics was defined by Dwyer *et al.* [38] as the '*use of engaging, embodied analysis tools to support data understanding and decision making*'. And while XR technologies and immersive environments are not named explicitly as part of this definition, they have all the characteristics for being used in that scope. Indeed, its use is implicit, given that, as we will see further ahead, XR's ability to provide users with engaging and embodied [77] experiences is a defining characteristic.

However, immersive analytics is a composite concept. By definition, it assumes the use of immersive technologies, but it also presupposes that their use is carried out with a very explicit objective - data analysis. In that scope, the more traditional 'visual analytics' aims to use interactive (typically screen-based) visual representations of data to support analytical reasoning and decision-making. Immersive analytics extends it by implicitly integrating XR technologies for providing a more spatial, collaborative, embodied, engaging and contextualized, multisensory data analysis [148],

The six cornerstones of immersive analytics [38] coincide precisely with the opportunities it offers compared to traditional data analytics. The first is the opportunity for in-person or remote collaboration between different stakeholders [16]. The second is the possibility of using multisensory stimuli, including haptic feedback [108], in addition to the more standard visual stimuli, which is the primary focus of traditional data analytics. The third is the possibility of spatial immersion both in a virtual environment or *e.g.,* by embedding data in the real surrounding environment, creating a 3D augmented workspace [99].

The fourth cornerstone of immersive analytics is the possibility of increased embodiment in data analysis [183]. This characteristic is enabled by the interaction possibilities offered by XR. Such possibilities go beyond the traditional mouse and keyboard and include natural interaction through *e.g.,* gestures, gaze [35], or voice [152].

The fifth is the possibility of enabling a more engaging experience, which is a direct result of the joint effect of the remaining five aspects of immersive analytics. Indeed, engagement in immersive analytics does not stem from any single characteristic but instead emerges from the combined effect of its various features [71].

Finally, the sixth cornerstone is the opportunity offered by immersive analytics to contextualize data with the real world [154]. This characteristic proved so impactful for data analysis that it gave rise to its own sub-area[1], situated analytics.

2.3 Situated Analytics

Situated analytics aims to frame data within the visual context of the object being examined [39], [147]. ElSayed *et al.* [40], [42] defines situated analytics as the organization and representation of data in relation to objects, places, or contexts in the real world.

The main objectives of situated analytics are [44], [154]: to better present information by immediately associating it with the object of analysis [47], to allow users to directly interact with that information through natural interaction, and to improve analysis by better contextualizing data [111].

The representation of data in the physical world, enabled by situated analytics, entails two fundamental concepts. The first is the 'physical data presentation', which consists of the visual elements that are superimposed to the object of analysis (*e.g.,* through XR) [178]. The second is the 'physical referent', which is the physical object or space to which the data refers to [130].

Situated analytics encompasses the concept of 'situatedness' [57], [178]. Situatedness is a property with multiple dimensions, including, for example, the spatial and temporal dimensions. In the spatial dimension, it expresses the extent to which the physical data presentation is physically (or conceptually) close to the physical referent. In the temporal dimension, it conveys the extent to which the data's temporal referent is close to the time of observation [154].

In that scope, Satriadi *et al.* [138] classified situated visualization in *proxied situated* visualization (also designated *proxsituated*) and *immediate situated* visualization depending on the type of situatedness perceived by the user.

[1] Some authors frame situated analytics as a complementary technique to immersive analytics, instead of a sub-area, as the two concepts have emerged at similar times [154].

The first uses technologies like VR or AR to enable data visualization over a proxied representation of the physical referent and the surrounding environment [44]. The second uses technologies like AR to represent data directly over the *real*/immediate physical referent. Both situatedness modalities offer an increased analysis contextualization, potentially improving analytical reasoning and decision-making [148].

Two concepts of *proxsituated* visualization are of special relevance for the present work. These concepts are 'level of detail' and 'spatial indirection'. The level of detail is the set of visual characteristics of the physical referent and the surrounding environment, including its textures, geometrical features, and lighting properties. A higher level of detail can mean, for example, the use of richer textures (visual detail), and a lower level can mean the use of flat-shading (no textures) [138].

Spatial indirection can be defined as '*an offset of space between two entities*' [138] within the *proxsituated* environment (for example between the data and the referent). A higher level of spatial indirection can mean *e.g.,* a larger distance between data representation and the referent. An example of a lower level of spatial indirection is the representation of data directly overlaid on the referent.

In addition to the levels of detail and spatial indirection, *proxsituated* visualization also entails other relevant concepts as identified in the model proposed by Satriadi *et al.* [138]. A concept deeply embedded in the definition of *proxsituated* visualization is the already mentioned use of digital referent proxies instead of the physical referent.

In parallel to spatial indirection, *proxsituated* visualization also addresses temporal indirection, which translates the time offset between the proxied referent state and its immediate counterpart state [138], [139]. In the case of data representation, temporal indirection entails the time offset between the data corresponding to the present state of the physical referent and data corresponding to a time in the future or the past. An example is the visualization of historical structural data (past) or structural data obtained with prediction models (future) embedded on a bridge or dam 3D model.

Another *proxsituated* visualization concept is the representation scale, which translates the transformation in scale between the proxied and the physical referents [138]. An example is the AR visualization of a down-scaled digital model of an urban district on top of a table to better observe the urban fabric's structure.

2.4 Dam Safety Control

Dam engineering is a domain dedicated to the conceptualization, planning, design, construction, operation/monitoring, rehabilitation/upgrade, and finally, decommissioning of dams.

Dam safety control is an area of dam engineering dedicated to ensuring dams' adequate performance and safe behavior during the operation/monitoring stage [125]. While dam safety control is commonly associated with the structural health monitoring of dams, its purpose extends well beyond that scope.

Indeed, structural safety is only one facet of dam safety control (although a very relevant one), which includes aspects such as hydraulic-operational safety (*e.g.,* of dam floodgates), environmental safety, geotechnical safety, and the implementation of emergency plans for downstream population safety (Emergency Action Planning /EAP). It also encompasses activities, such as outreach initiatives concerning the functional and hydro-environmental facets of dams [3]. Likewise, it incorporates activities such as social impact assessment, including the promotion of public awareness of the impacts of dams on water and energy resource sustainability.

The monitoring of dams during their operation includes, generally, three types of activities. The first is instrumentation monitoring/observation. This activity is concerned with analyzing data acquired through sensor networks. These are installed throughout the dam structure, its foundation, and the surrounding areas. Sensors installed in dams can typically measure the following quantities: upstream and downstream water levels, displacements in the structure, displacements in the foundation, relative movements in cracks and construction joints, air temperatures and humidity, structural elements temperatures, foundation temperatures, structural strains, subpressures in the foundation, drained and infiltrated flows and dynamic accelerations [120].

Registering the large set of quantities requires multiple types of sensor networks. Water levels are measured using limnimeters installed upstream and downstream. Temperatures and humidity are registered using meteorologic stations equipped with thermohygrographs, thermometric probes, and udometers (precipitation). Horizontal and vertical displacements in the structure are typically registered using plumblines (Figure 2.5 (b)), Global Navigation Satellite System (GNSS) equipment (Figure 2.3) but also geodetic methods through triangulation employing a network of fixed marks [119] (Figure 2.4).

Horizontal and vertical displacements in the foundation are measured using bar extensometers. Relative movements in the concrete, cracks, and joints are recorded using *Carlson* type elastic wire strain meters embedded in the concrete and joint meters. Temperatures inside the concrete structural elements are measured using electrical-resistance thermometers. Drained and infiltrated flows are registered using drains and volume totalizer spouts. Foundation subpressures are measured through piezometers. The dynamic behavior of the dam is tracked using accelerometers, which register the response under seismic actions and ambient/operational excitation [20].

Figure 2.3: Location of the GNSS receivers at the *Cabril Dam* in Portugal (left) and detail of the GNSS antenna at the top of the dam (right) (LNEC).

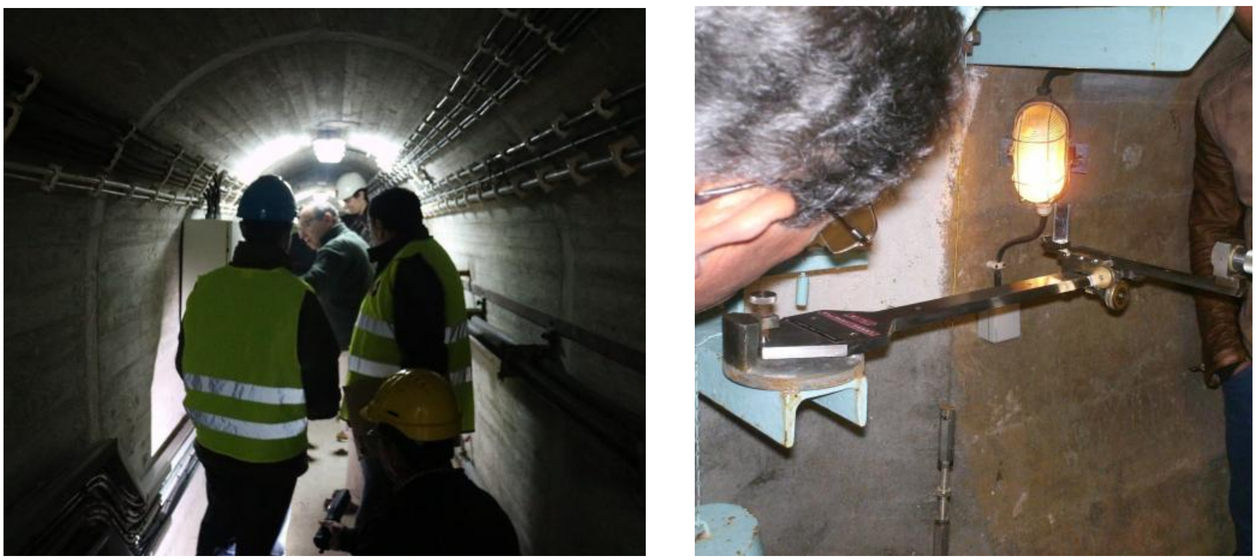
(a) **(b)**

Figure 2.4: Using a total station theodolite (a) to determine the exact position of the fixed geodetic marks (b) installed in the downstream face of the *Cabril Dam* in Portugal [157].

The water's hydrochemical characteristics in the upstream reservoir and downstream are also typically monitored. They can be measured automatically using on-site sensors or, more often, manually during periodical inspection campaigns. These characteristics include aspects such as electrical conductivity, redox potential, temperature and water aggressiveness index for cement in concrete or injection grouts [73].

The second activity encompassed in dam monitoring is visual inspection. Visual inspection campaigns are carried out periodically *on-site* by observation technicians with the support of dam engineers. They mainly aim to detect deterioration signs, including structural and constructive pathology. They also aim to verify the proper functioning of the sensor/observation system itself [120]. Visual inspectors pay special attention to the superficial state of structural and non-structural elements. An example of a notable aspect to take into account is the existence, location, extension, and other characteristics of cracks.

Visual inspections are carried outside the structure, namely through the walkways typically existent in the downstream face of dams, but also inside the structure itself, namely by taking advantage of the network of inspection galleries that typically traverses these structures (Figure 2.5). In order to inspect inaccessible areas outside the dam, inspection technicians have been increasingly resorting to the use of Unmanned Aerial Vehicles (UAVs) equipped with high-resolution cameras, depth cameras, and laser-scanning technology [120].



(a) (b)

Figure 2.5: Dam safety control experts carrying out an inspection campaign from inside the maintenance galleries of the *Cabril Dam* in Portugal (a) and using an optical coordinometer to read the displacement in a plumbline (c) (LNEC).

A third relevant activity of dam monitoring is analyzing and forecasting the dam's behavior based on numeric and semi-empiric models. These models can *e.g.,*be used to simulate the static and dynamic behavior of the dam structure considering different types of loads. The predicted behavior is then compared with the measured behavior to assess if the dam behaves as expected, within the normal parameters [118].

Chapter 3

Related Work

In this chapter, we present relevant existing research work related to the central themes of this thesis. We start by addressing related studies concerning using XR in AEC. We then focus on existing research in immersive visualization in dam engineering. Next, we address prior studies on situated visualization. Then, we concentrate on scientific work that concerns using *proxsituated* visualization and analysis in distinct domains. Furthermore, we explore how the particular aspects of visual detail and data indirection have been addressed in recent work. Moreover, we address previous comparative studies of extended reality with desktop computers/2D screens. Finally, we carry out a general discussion of the themes addressed in the framework of the main objectives of our thesis work.

3.1 Extended Reality in AEC

The AEC area has been an important motor in the development of XR technologies. XR has been applied extensively across several domains of the central thematic lines of AEC: architecture, engineering, and construction. In this section, we present relevant work in that scope applied to fields such as engineering design, architectural design, construction inspection, construction assistance, and construction safety.

In the scope of engineering design, Isobe and Yang [72] proposed the use of virtual environments for visualizing the behavior of nonstructural components of buildings (*e.g.,* panel ceiling or furniture) when subject to seismic excitation. They developed a VR application incorporating finite element behavior models. They demonstrated the system by simulating the impact of a high-intensity earthquake in a 10-story reinforced concrete building model. This type of system can help engineers and architects visualize the behavior of nonstructural components when designing buildings.

The design of road tunnel rescue rooms was addressed by Moscoso *et al.* [113]. During the design process of such rooms, they used virtual environments to understand how different design options and spatial factors could affect users' acceptance. With that objective, they developed a system where users can experience a simulated emergency scenario in VR. A user study using the system allowed them to conclude that factors such as lighting and using separate areas positively affect users' feelings of safety.

Souza and Fabricio [150] addressed the use of virtual environments for pre-design evaluation of building performance. They developed an application that allows users to roam through healthcare facilities containing functional design errors to assess the impact of those errors on user satisfaction.

In the context of architectural design, Beatini *et al.* [11] analyzed how virtual environments could be used to address the emotional impact of adaptive facades [4] in building occupants. With that objective, they built a VR application that allows users to roam the indoor environment of buildings with adaptive facades. The application allows the simulation of the indoor visual impact of facades with different coverage ratios, opacity, and patterns.

Ze and Yu [182] focused on using virtual environments for interior design. In particular, they addressed the VR simulation of the visual impact of sunlight throughout the day and the outside natural scenery properties in interior compartments.

In the scope of landscape design, Ha *et al.* [61] addressed how immersive visualization could be used to teach design details in landscape architecture. They developed a user study comparing the user experience of roaming virtual landscape models with VR HMDs and with desktop computers. Their findings indicate a better spatial perception and a higher sense of realism with the VR alternative.

In recent years, relevant scientific work on applying XR to construction inspection has also been carried out. Such an example is the work by Melnyk *et al.* [109], who focused on using AR for enhancing the reporting of inspection results carried out in campaigns during tunnel construction. They developed a prototype that allows inspectors to attach virtual information panels to relevant locations in space where structural anchors are located inside the tunnel. The inspector uses these panels to enter relevant information regarding the results of structural tests carried out for each anchor during the inspection (Figure 3.1).

Tan *et al.* [153] addressed the inspection and management of building defects using AR. They propose a framework that integrates AR with Building Information Modeling (BIM) and computer vision for detecting and tracking defects in real-time. Each defect is then linked to an entry in the BIM database to obtain detailed information regarding the specific structural or nonstructural components being inspected. Likewise, Liu *et al.* [91] associated AR to BIM for *on-site* construction inspection. In that scope, they propose a new algorithm for mapping point cloud data with its BIM database information counterpart.

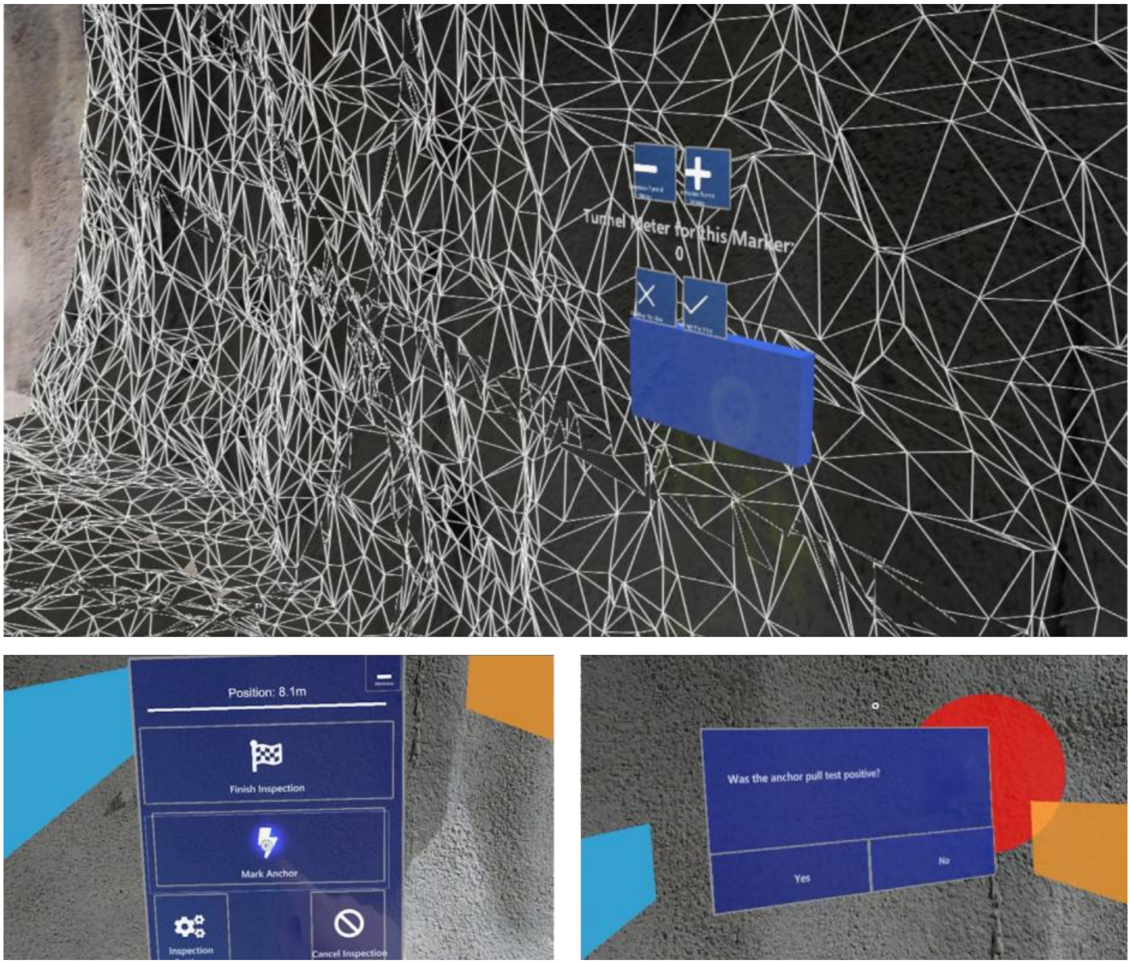


Figure 3.1: Using AR for reporting the results of tests in structural anchors inside tunnels during inspection campaigns [109].

The effective integration between XR and BIM in the scope of transportation infrastructure management was also addressed by Alhady *et al.* [6]. They propose a workflow for engineers and other stakeholders to visualize and monitor the distinct stages of construction of road bridges and viaducts, using both AR and VR.

XR has also been studied in the scope of construction task assistance. Fazel and Adel [50] proposed using AR to reduce human errors in timber connection execution. They developed a system to track the position and orientation of power tools used for timber construction. The system can superimpose to the raw timber component virtual markings indicating the exact points where the worker has to drill or apply joint screws. It also enables the display of virtual levels to guide the workers on the correct orientation angle for the power tools. Moreover, because the system tracks both the geometry of the raw timber component (using fiducial markers) and the power tool, it automatically turns the power tool off when it detects an orientation or position misalignment (Figure 3.2).

Figure 3.2: Using AR for assisting workers in timber connection execution tasks by giving visual indications of the points where the worker has to drill or apply joint screws. The system proposed by Fazel and Adel [109] can also track power tools to detect positional and orientation errors.

Rogeau and Rad [135] also addressed using XR in timber joint assembly. In particular, they studied the use of AR for human-robot interaction in timber construction. They developed a system that can give the worker wearing an AR headset holographic assembly instructions projected over the timber components. The system also enables collaboration between the robotic and human workers by automatically allocating the assembly tasks to one or the other, according to their abilities.

The use of AR for assisting operators in road maintenance tasks was the focus of the study proposed by Bavelos *et al.* [10]. They implemented a system for *on-site* use, which can guide the road maintenance operator, wearing an AR headset, in complex tasks by enabling the display of instructions overlaid to the road and used machinery (Figure 3.3).

The area of construction safety training with XR has also been the target of multiple

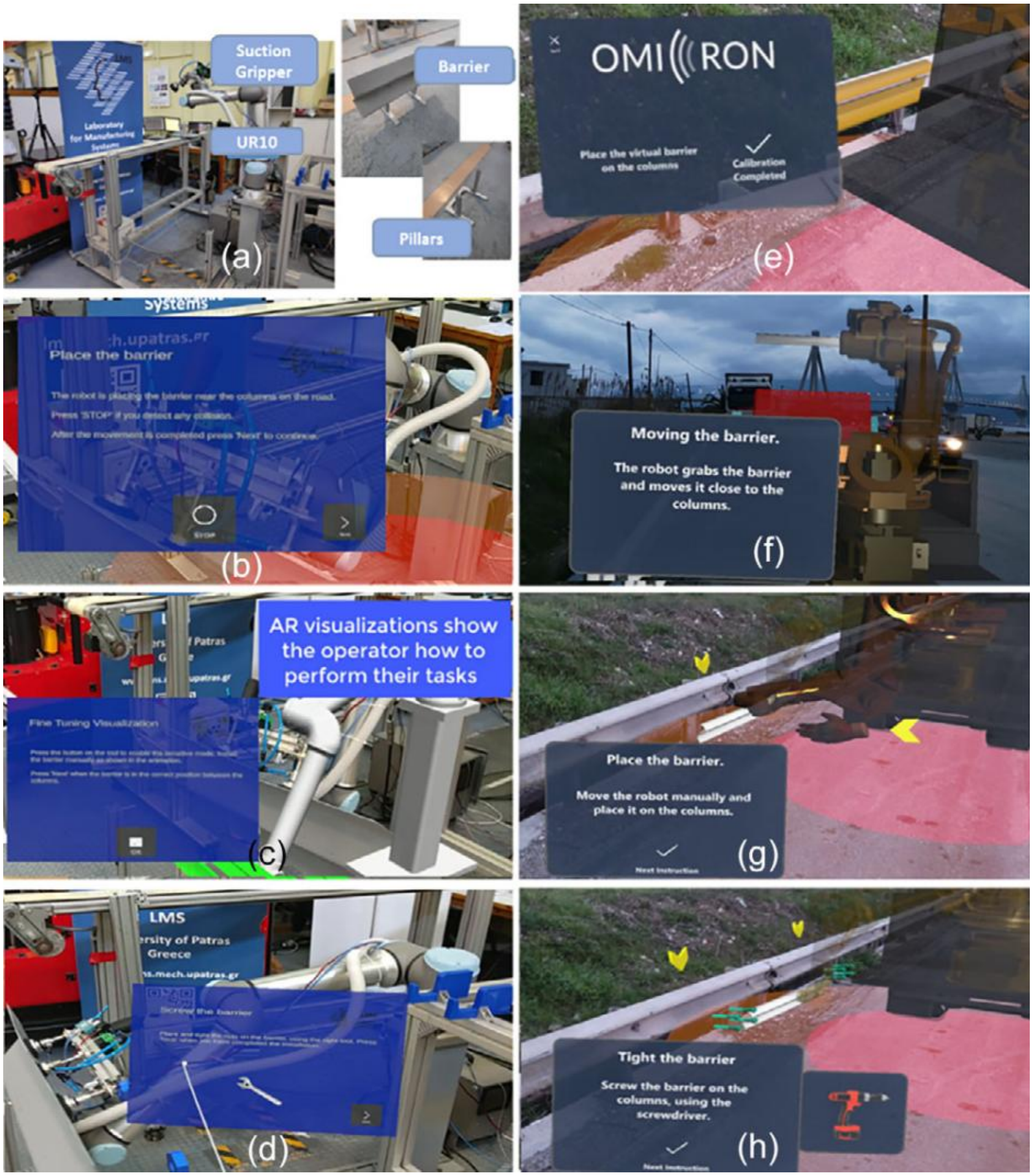


Figure 3.3: The AR system proposed by Bavelos *et al.* [10] can provide road maintenance operators with instructions on carrying out complex *on-site* tasks.

scientific studies. An example is the work developed by Hussain *et al.* [69], who applied VR for simulating hazard scenarios to prevent struck-by accidents in construction workers. They conducted a user study on the relation between attentiveness and situation awareness on construction sites (Figure 3.4).

Moreover, Chen *et al.* [21] proposed using AR headsets for hazard prevention directed at heavy construction machinery operators. They developed a system that uses the headsets'

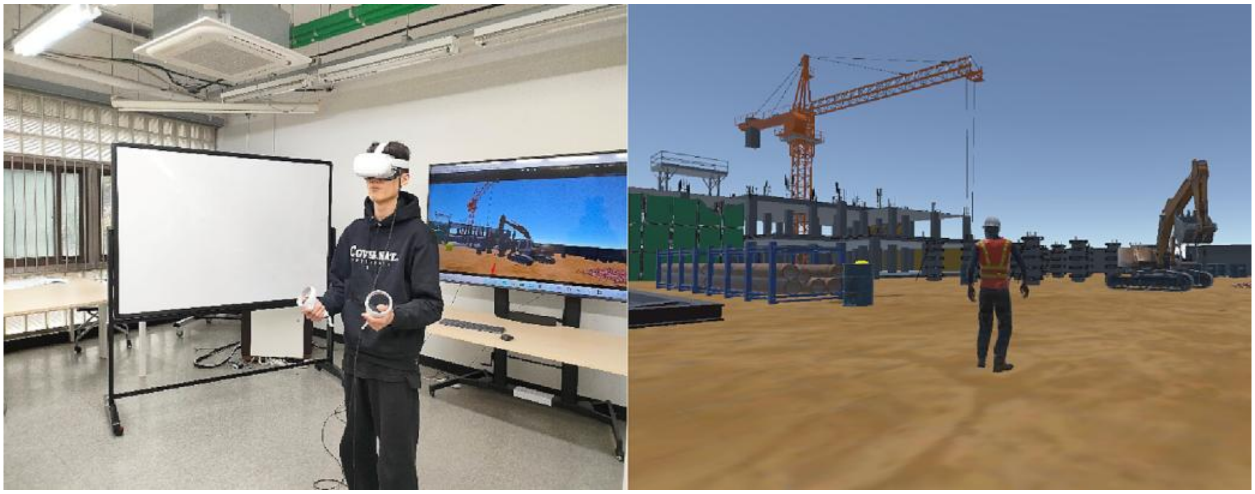


Figure 3.4: Hussain *et al.* [69] addressed the use of VR for simulating hazard scenarios in construction sites.

hand and eye-tracking functionality to detect abnormal operators' behavior that could lead to accidents. The system enables visual and auditory alerts when it detects that the operator cannot safely operate the construction machine.

3.2 Immersive Visualization in Dam Engineering

As we have seen in the previous section, XR has been used in immersive visualization in many AEC domains. Dam engineering immersive applications, however, have yet to be fully explored. Some of the reasons for this lack of adoption could be related to difficulties brought about by dam structures' intrinsic characteristics. Such characteristics include its larger scale when compared with other civil structures. They also include the homogeneity of its surface, namely on gravity concrete dams (the issues associated with this feature will be addressed in Section 4.2). Furthermore, dams are also typically remote and frequently difficult to access structures, making *e.g.,*data acquisition for 3D modeling more cumbersome.

The combination of such factors can hinder on-site applications, and relevant steps entailed in developing *off-site* XR applications, such as the above-mentioned accurate structure modeling. Nevertheless, the increasing use of UAV and Light Detection and Ranging (LiDAR) technology in dam positional data acquisition has made 3D modeling more manageable. This section will address some examples of studies concerning applying XR technologies to immersive visualization in dam engineering.

It was precisely in the scope of dam modeling for use in XR-powered applications that some recent studies were focused on. In particular, they addressed the process of transferring data from engineering project elements to immersive visualization applications. An example of such studies is the work developed by Cheng *et al.* [22]. They focused on establishing a workflow to facilitate modeling dam reservoirs' underwater terrain. This process is especially relevant as the underwater portion of the terrain encompassing the reservoirs is often not included in topographic survey campaigns that are restricted to using LiDAR and total stations. To obtain a point cloud, they used multibeam echosounders [95] and side-scan sonar systems [8]. They then used this data to generate a detailed model of the reservoir bed, designed to be integrated in VR environments. Such a process applied through the years will result in the possibility of visualizing the fluctuations of silt accumulation in reservoirs over time in an immersive environment.

Likewise, Lin and Chen [88] streamlined the migration of digital project blueprints of gravity dams to 3D models aimed at being integrated into immersive environments. Moreover, with the same objective, Zhao and Zhang's work [184] focused on enhancing the transition process from digital engineering drawings to 3D models ready to be integrated into VR applications. The objective of this process was to facilitate the simulation of the several stages of the dam's construction. Wang *et al.* [170] proposed a similar process but directed at generating steel slit dam [78] 3D models for VR applications directed at *off-site* inspections.

The process of converting experimental groundwater flow data to 3D models, ready to be used in AR environments, was addressed by Marques *et al.* [98]. They superimposed these virtual models to physical models of embankment dams with the objective of better visualizing the seepage phenomena [132].

Using immersive visualization in dam construction supervision and monitoring has also been the target of previous scientific studies. An example is the work carried out by Lin *et al.* [90], which addressed the use of AR in earth and rockfill dam [129] construction monitoring. They focused on assessing the quality of earth compaction in real-time. With that objective, they used compaction roller machines' positional sensor data to superimpose virtual idioms, representing the current earth compaction level, to the actual dam being built.

In the scope of dam construction supervision, Wang *et al.* [169] focused on using AR technology to visualize the operation of cable cranes operation, with the objective of tracking and improving its productivity. They propose a method for visually tracking and optimizing the movement of crane buckets to reduce operational costs.

Ren *et al.* [133] addressed the integration of AR in inspecting and monitoring concrete arch dam construction. They focused on representing, superimposed to the dam in construction, digital information comparing as-built versus as-designed. They use automatic structural geometry feature extraction and compare it with the geometrical data in the project specifications. Construction supervisors and inspectors can use the system to identify *on-site*, positional discrepancies during the construction process.

Zhong *et al.* [187] addressed the use of AR to overlap a representation of the sequential construction stages of core rockfill dams to reality. They propose a system that allows supervisors to see a visual representation of the construction schedule superimposed on the construction works in progress.

As mentioned in Chapter 2, the dam safety control domain aggregates a set of activities that are not restricted to data analysis. Indeed, it also encompasses activities such as promoting public awareness of the importance of dams in water and energy resources sustainability. It also includes outreach initiatives concerning the functional and hydro-environmental facets of dams.

In that scope, Spero *et al.* [151] developed a study on realistic modeling and simulation of dam failures (Figure 3.5) in VR. They focused on conveying dam safety risks to the general public and policymakers. With that objective, they build accurate virtual environment simulations of historical dam disasters. They used precise hydraulic and structural simulation theoretical behavior models. They also employed drone technology to acquire detailed geometry of dams and the surrounding environment.

Janovsky *et al.* [74] used VR to relay the landscape impact of dam construction to school children and the general public (Figure 3.6). They simulated the geomorphic changes of the Vltava River valley in the Czech Republic over 60 years, using a large terrain virtual environment partly generated using procedural modeling.

Likewise, Macchione *et al.* [96] addressed the use of VR in public awareness of the importance of dams in flood prevention. They focused on building a realistic simulation of the urban impact of water rise in a hydrographic basin (Figure 3.7). The 3D modeling of the basin was carried out using detailed spatial data obtained using LiDAR. The virtual environment aims to promote the active participation of the different stakeholders in flood management planning.

Virtual environments have also been addressed in the scope of dam monitoring. One example is the work proposed by Wang *et al.* [171], which focuses on using 3D environments for visualizing the different components of dams. They developed a system that allows users to navigate through the structure of dams, observe the location of sensors, and visualize the values registered in those sensors over time. While not XR per se as it was designed for use in desktop computers/2D screens, the system has similar objectives to some of the systems that will be discussed further in Chapter 4. Goff *et al.* [59] also addressed dam monitoring in their work, but employing touch devices such as smartphones and tablets. They focused on using AR for visualizing relevant maintenance information superimposed to hydraulic components of small dams, like pipework and valves.

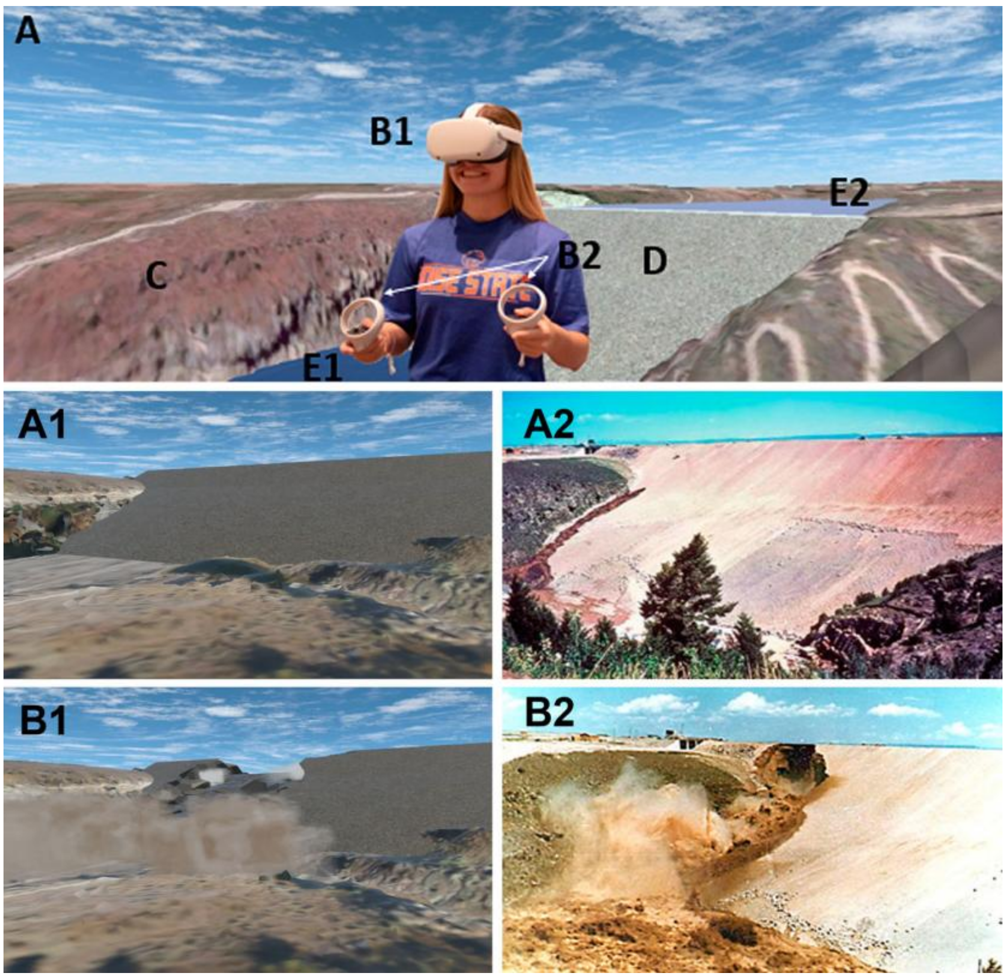


Figure 3.5: Visualizing the *Teton Dam* failure simulation time series in an immersive environment [151] (top, left) and real images of the incident (right).

Figure 3.6: Demonstrating the mechanisms of dam reservoir filling using VR during a tour of primary school students [74].

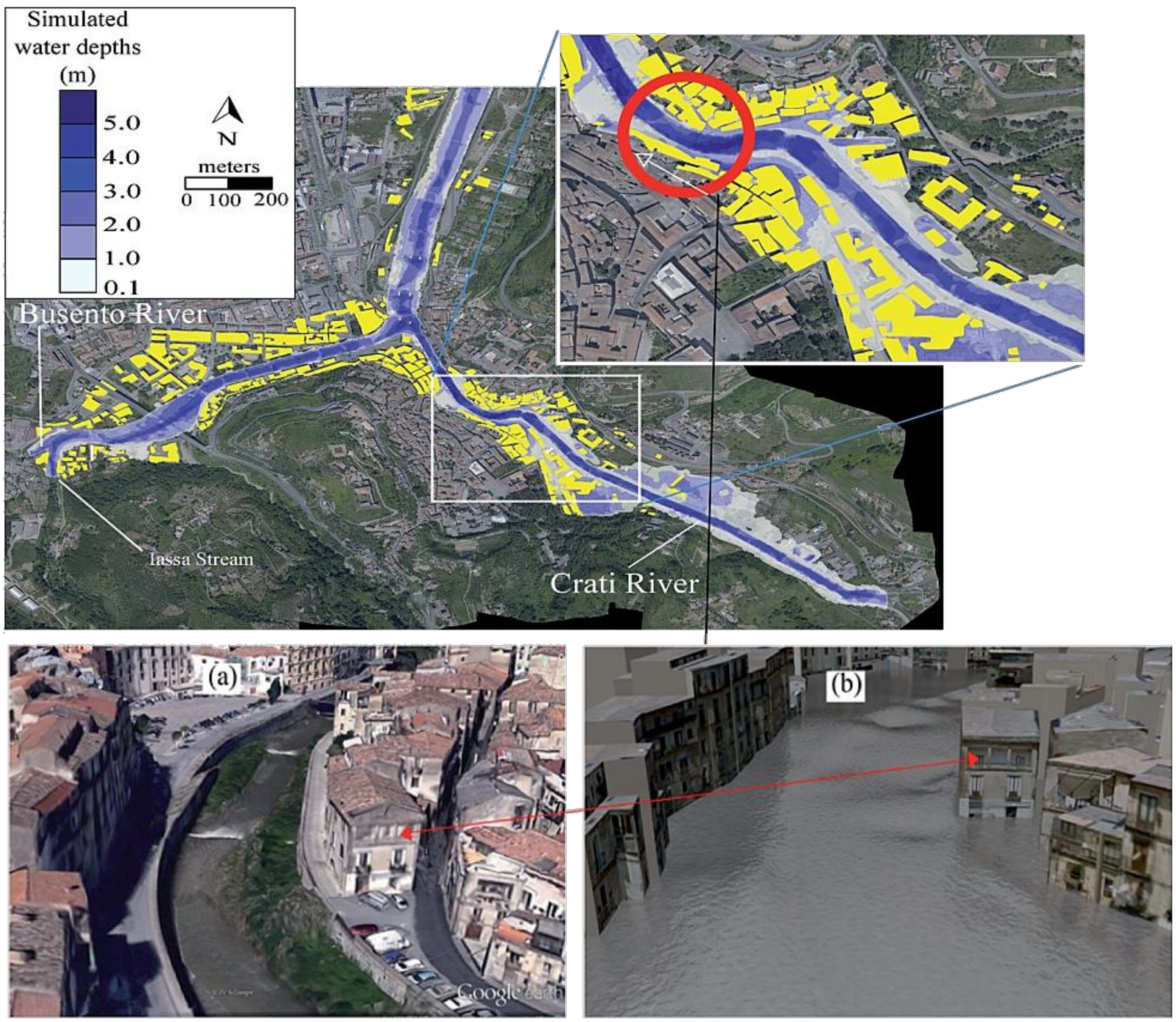


Figure 3.7: Promoting public awareness of the importance of dams in flood prevention by using a VR simulation of the urban impact of water rise in a hydrographic basin [96].

3.3 Situated Analytics

As we have seen in Chapter 2.3, situated analytics is a subarea of immersive analytics focused on representing data in its spatial and semantic context [176]. With the assistance of AR technologies, data can be represented as a virtual overlay to the real object being visualized/analyzed [175], [178]. Data can also be visualized in a situated context with the help of VR by using a representation/model of the object being analyzed instead of the real object [138]. Situated visualization, applied to a variety of areas and domains, has been the focus of previous research [17], [104], [147], [154].

An example of situated visualization is the system proposed by Behzadan and Kamat [12]. They address the application of AR in the superimposition of virtual elements representing the geometry of municipal underground infrastructure to the pavement of urban streets. Such a mechanism allows municipal workers to visualize how underground utility lines are distributed along sidewalks and roads before initiating underground repair works and excavating the pavement. Such a system provides a practical way to situate municipal infrastructure data. By directly contextualizing data over the object of analysis, the system avoids manually establishing the correspondence between utility blueprints and the urban setting.

ElSayed *et al.* [40], [42] focused on interaction and visualization techniques for situated analysis in contexts where embedding data with the physical environment was relevant. They developed a context-aware design pattern [41], [43], which promotes a seamless transition between the physical space and the information being analyzed. ElSayed *et al.* [41] also validated these concepts in a shopping experience context. They compared an AR situated approach, where relevant information would appear superimposed to products with a conventional shopping experience. They determined that the former had more advantages in terms of speed and accuracy than the latter. Likewise, Abao *et al.* [1] also addressed situated analytics in shopping scenarios. They used AR-powered mobile devices, like smartphones and tablets, to superimpose nutritional characteristics to food products in supermarkets. Their system targets users with health conditions such as diabetes, allowing them to select food products compatible with their condition.

An AR mobile application, directed at representing soil conditions data superimposed on real agricultural terrains, was proposed by Zheng and Campbell [186]. The system is directed at farmers for *on-site* situated visualization of relevant agricultural data, including soil analysis results and subfield soil characteristics.

Alallah *et al.* [5] focused on visualization and interaction techniques for enhancing the exploration of video data in situated contexts. They investigated the performance characteristics in visual analytic tasks with video data in situated and non-situated settings.

Their results show that in that context, users benefit from environmental cues. Moreover, Berger [14] propose using sonification techniques to better convey continuous spatial data in situated analytics. They exemplify the application of these techniques in the context of the visualization of air quality records datasets and emphasize how they can improve data perception.

Buschel *et al.* [19] proposed a situated visualization toolkit for the visualization and analysis of spatiotemporal interaction data. The toolkit uses AR headsets for tracking user interactions and trajectories. The users' movement is then represented in space through trajectories and trails. It also uses 2D idioms, like heatmaps, attached to surfaces to represent *e.g.,* user touch data with that surface. Fleck *et al.* [54] also proposes a toolkit for situated analytics. They apply this toolkit to hot air emissions visualization in an industrial installations context (Figure 3.9).

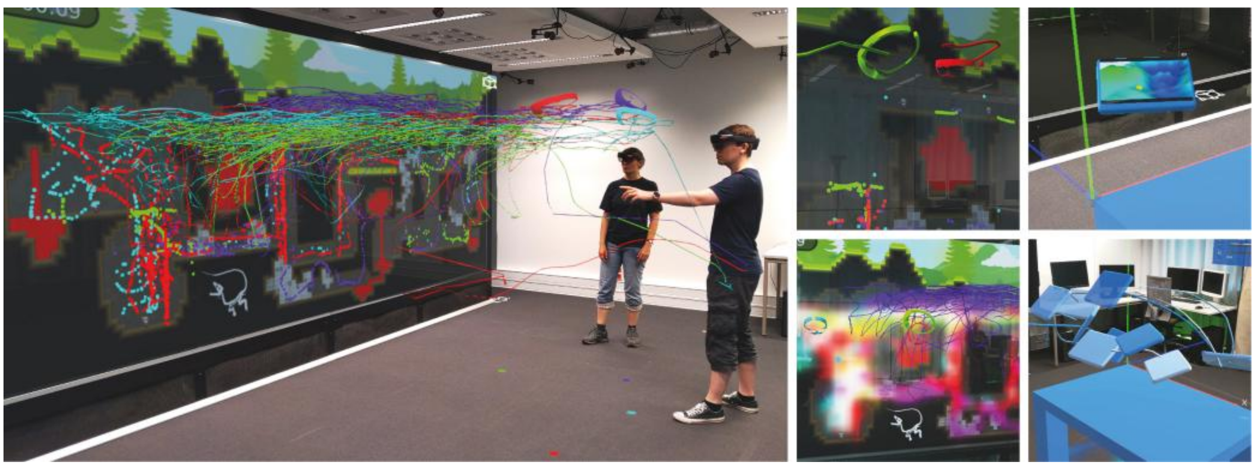


Figure 3.8: Situated visualization of spatio-temporal interaction data [19].

Figure 3.9: Using AR for situated visualization of industrial equipment, for augmenting an instrumented ventilator [54].

Moreover, Lin *et al.* [89] applied situated analytics techniques to the real-time visualizations of free throws of basketball athletes. They propose the representation of the ball's trajectories in space, offering immediate visual feedback on a player's shot performance. They experimented with experienced basketball players, wearing *Microsoft HoloLens* headsets running the proposed visualization. They concluded that this type of situated visualization can help athletes improve their accuracy.

In the scope of situated spatial representations, Guarese *et al.* [60] addressed the visualization of electromagnetic radiation data inside anechoic chambers. They developed a prototype for *Microsoft HoloLens* headsets that allows *in-situ* visualization of 3D field topologies of different radiation frequencies.

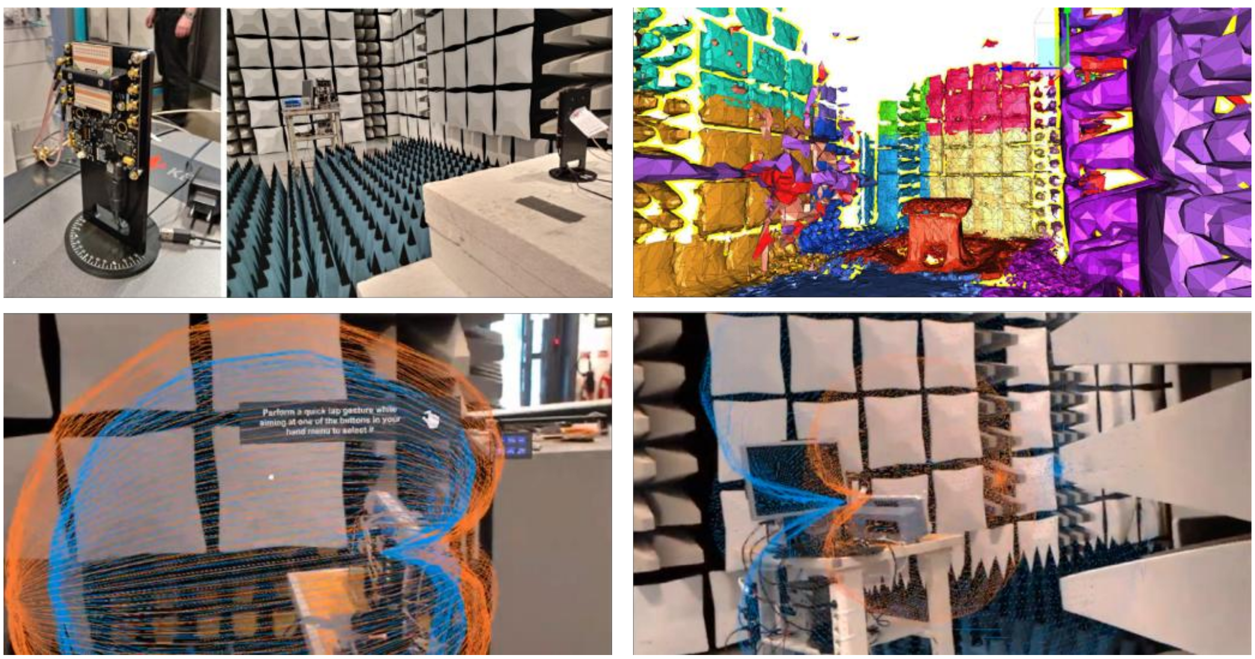


Figure 3.10: Situated visualization of electromagnetic radiation data inside an anechoic chamber [60].

The translation of interaction and visualization techniques from desktop to situated visualization, enabled by AR mobile devices, was the focus of Zhao *et al.* [185]. They also compared the different effectiveness aspects of the two visualization modalities in scatterplot and storyline visualizations.

Ens and Irani [47] studied the effectiveness of data representation in situated visualization with AR headsets. They addressed aspects such as virtual window layout configurations and their integration into the augmented user's surroundings. Furthermore, they analyze different techniques for representing visual links between data in distinct windows. Also, in that scope, Wen *et al.* [173] addressed how different types of windows layout configurations compared in a situated visualization context.

Note: The related work described in this section was addressed by Verdelho Trindade *et al.* [164], [165].

3.4 ProxSituated Visualization

The concept of situated analysis does not necessarily mandate the use of AR or the real referent. As we have seen earlier, *proxsituated* environments use proxy representations of the physical referent instead of the actual object of analysis. Different extended realities, such as VR, can be used for such a purpose. Indeed, realistic (or less realistic, more symbolic) virtual proxies for physical referents can effectively be used in XR environments for mimicking the real object of analysis, as proposed by Satriadi *et al.* [138].

Such an example of *proxsituated* visualization is the immersive analytics VR system developed by Nouri *et al.* [117]. The system is directed at the situated analysis of buildings' facade durability by experts and non-experts. In a *proxsituated* virtual environment, it allows users to analyze how biocide availability is affected by rain, the facade's geometric structure, or the building's orientation. The system uses data from on-site sensors and chemical analysis of the facade materials over time. This data is represented, using symbolic time series, directly over the facade of the building model (which was obtained using 3D reconstruction techniques with photographic textures), near the area it respects, as shown in Figure 3.11.

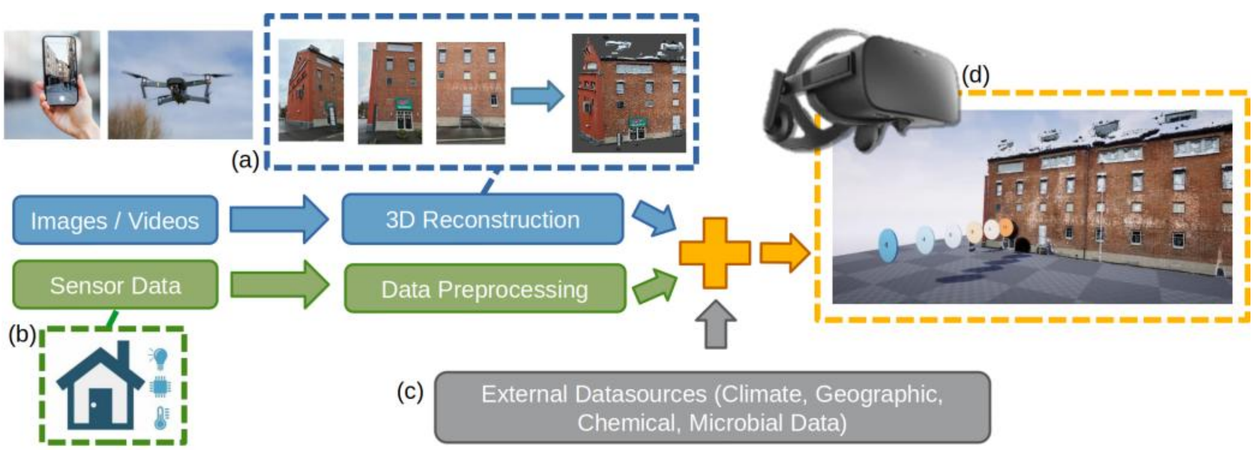


Figure 3.11: The process proposed by Nouri *et al.* [117] for obtaining buildings 3D models, associating and representing time-series sensor data directly over its facades.

Also, Ens *et al.* [46] built a *proxsituated* VR prototype directed at establishing a visual connection between smart devices in built environments. In particular, the '*Ivy* system allows the user to visualize the data flow between sensors and actuators in a virtual representation of the different rooms inside a house. In that scope, *Ivy* users can manually establish logic links between virtual devices. These changes will have correspondent repercussions on the actual smart installation.

Iglesias *et al.* [70] focused on developing an immersive system for structural analysis of railway tunnels. The system uses precise and photorealistic models of tunnels to faithfully reproduce the sensation of being in front of the object of analysis. These characteristics allow users to visualize the structural defects found on the tunnel's surface while off-site.

The previously mentioned examples of *proxsituated* visualization use an egocentric approach. This approach means that while the referent is proxied, the user viewpoint within those systems corresponds to the actual viewpoint the user would have if they were in front of the physical referent. The limitations of such systems were highlighted by Martins [102]. The authors noted that these limitations were relevant not only for VR-powered *proxsituated* environments but also for *proxsituated* systems that use AR. The same limitations apply even more obviously to situated visualization systems using immediate referents.

To mitigate egocentric viewpoint limitations, Martins *et al.* [103] address multi-perspective views, transitional interfaces, and multimodal information. They highlight how the transition between distinct static and dynamic feeds of several real and virtual viewpoints within the same display can be relevant in that scope. The proposed techniques include the seamless transition from an AR egocentric view to other relevant VR views without changing physical location.

With the same objective of hindering egocentric viewpoint limitations, Martins *et al.* [24] further proposes, in the case of immediate situated systems, the transition between distinct camera feeds to give the user the feeling of being in different places around the physical referent. They also propose combining an egocentric viewpoint of the physical referent with a wider, more distanced viewpoint using a virtual rendering of the referent. They exemplify this concept with a prototype that allows a user inside a compartment to transition its viewpoint to a bird's eye view of the building they are in, using a virtual representation of that building and surrounding landscape.

Martins *et al.* [101] developed a system for situated air quality visualization (Figure 3.12). The system represents, over the real world, real-time air quality data using AR and combines immediate situated with *proxsituated* features to overcome egocentric viewpoint limitations. In particular, it can display a VR view from above the area where the user is currently located. Such combined use of different modalities of situatedness resulted in an improved analytic performance. They registered a 42% task completion time decrease when comparing the use of immediate situated features (AR) with the combined use of immediate and *proxsituated* features (AR+VR).

Figure 3.12: A system for situated air quality visualization. Immediate situated approach using AR (top image) and the combined use of immediate and *proxsituated* features using AR+VR (bottom images) [101].

Weidinger *et al.* [172] work focused on how distinct modalities of data representation within a *proxsituated* environment influenced data analysis performance. In particular, they addressed the impact of the distance of the data representation to the object of analysis. They used an immersive analytics prototype to visualize spatiotemporal racing data. They asked five expert users to perform cornering performance analysis using three distinct ways of representing velocity, throttle, and brake data in relation to the racing track. They compared the use of conventional line charts, situated 3D graphs directly represented over the racing track, and a hybrid way which used situated 3D graphs together with line charts (Figure 3.13). The results showed that users preferred the hybrid visualization and highlighted the usefulness of the embed 3D graphs in understanding differences in distances between events.

The form of representation of digital proxies and data was addressed by Cornel *et al.* [29], which developed a real-time technique for visualizing large-scale terrains based on adaptive

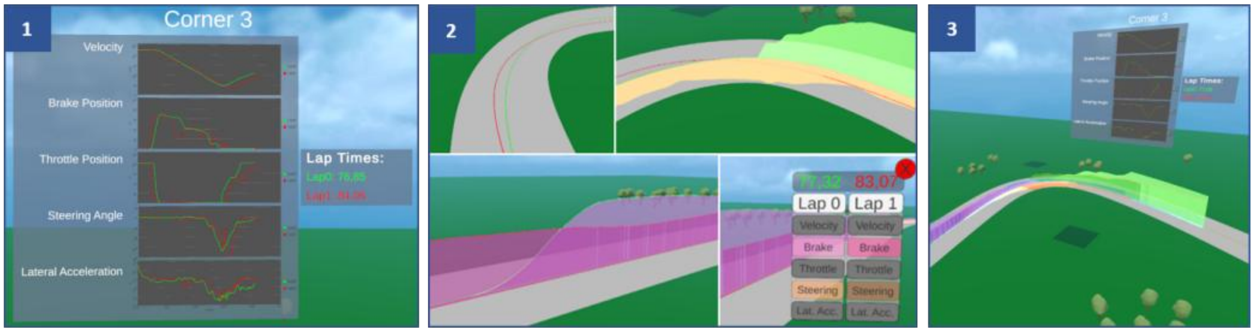


Figure 3.13: Three different ways of visualizing racing data on a *proxsituated* racetrack: with line charts (left), with 3D area charts directly over the track and combining the two visualizations [172].

height fields. This technique was designed for interactive applications and was tested with visualizations of stormwater runoffs on river valleys, failing floodwalls in urban scenarios, and tsunami impacts on cities. The technique was applied to flood and heavy rain simulation and data visualization of a 300 km2 portion of the Danube River in the Marchfeld region in Austria. The technique allows users to navigate through a high-fidelity terrain model with realistic water behavior and visualize flood data directly superimposed to the proxied referent. The data representation is carried using, *e.g.*, the coloring of water and buildings by water depth as represented in Figure 3.14.

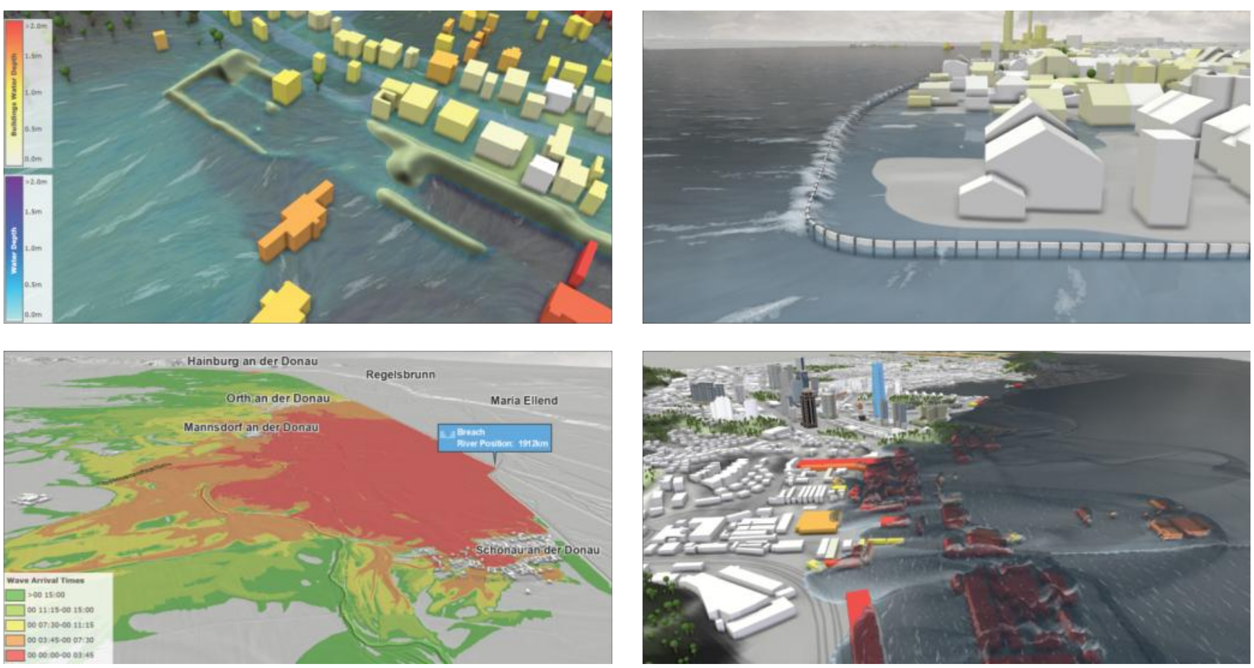


Figure 3.14: Large scale *proxsituated* visualization of flood impact at local and regional scopes [29]. Areas and buildings with higher flood impact risk are highlighted in red tones.

Ready *et al.* [131] studied the analysis of river management in a big data framework. They developed a VR *proxsituated* visualization that allows users to directly explore data from

18,000 weather sensors over a representation of the analyzed river. This data concerns water quality, water level, snow, and rainfall, among other properties. Each property is represented along the river surface using 3D bar chart with horizontal coordinates corresponding to the sensor location and height corresponding to the property value (Figure 3.15). The user can select a specific bar and visualize the evolution of recorded values over time in a 2D line chart.

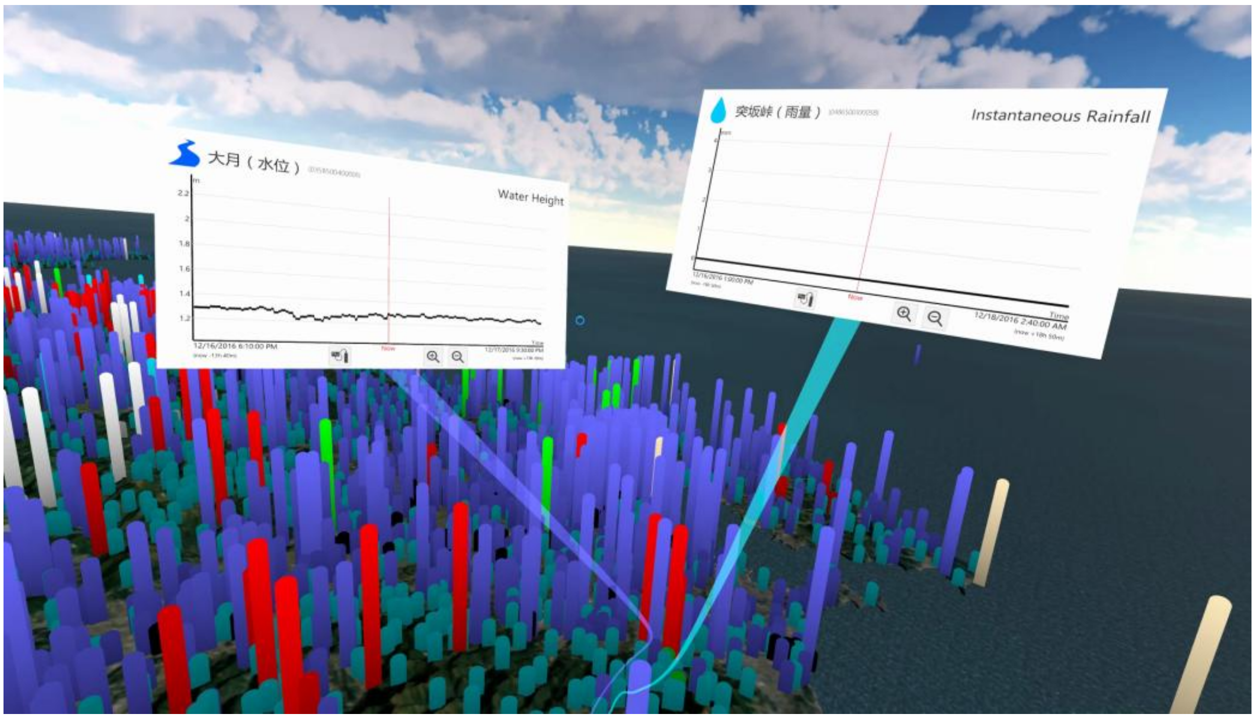
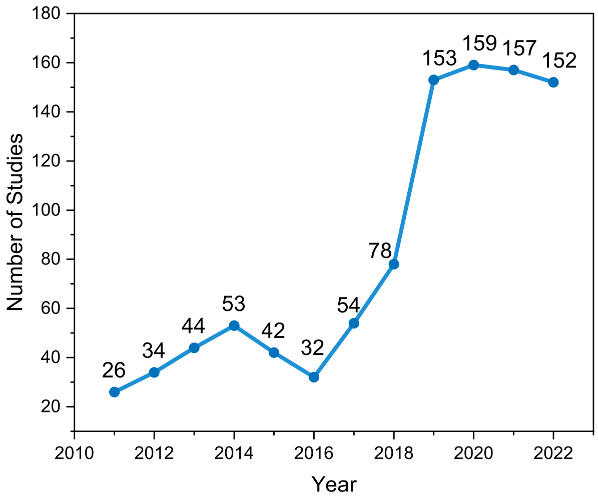


Figure 3.15: A *proxsituated* visualization of river management data with multiple levels of data spatial indirection: directly over a virtual representation of the referent and in 2D charts displayed in floating panels [131].

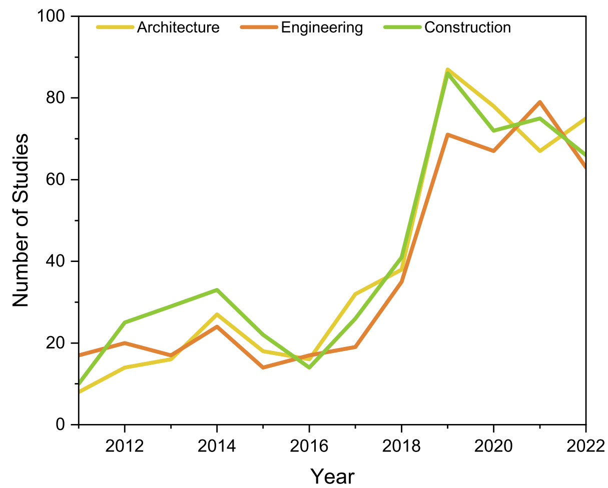
3.5 Discussion

In the previous sections, we addressed existing research related to our thesis. We first started by addressing how the AEC area has been the source of many advancements in the practical use of XR. We described relevant examples in AEC domains, such as engineering and architectural design, construction inspection, assistance, and safety.

However, in 2023, we carried out a broad systematic literature review in the scope of XR in AEC [161]. In this work, we analyzed 11242 studies and selected 983 relevant papers published between 2011 and 2022. This review enabled us to identify significant trends of XR in AEC that have emerged over the past decade. Figures 3.16, 3.17 and 3.18 illustrate those resulting trends.



(a) Evolution of the number of relevant primary studies published in the last decade [161].



(b) Evolution of the number of relevant primary studies, by AEC area, published in the last decade [161].

Figure 3.16: Tendencies registered in the last decade concerning the scientific production in the scope of XR in AEC [161].

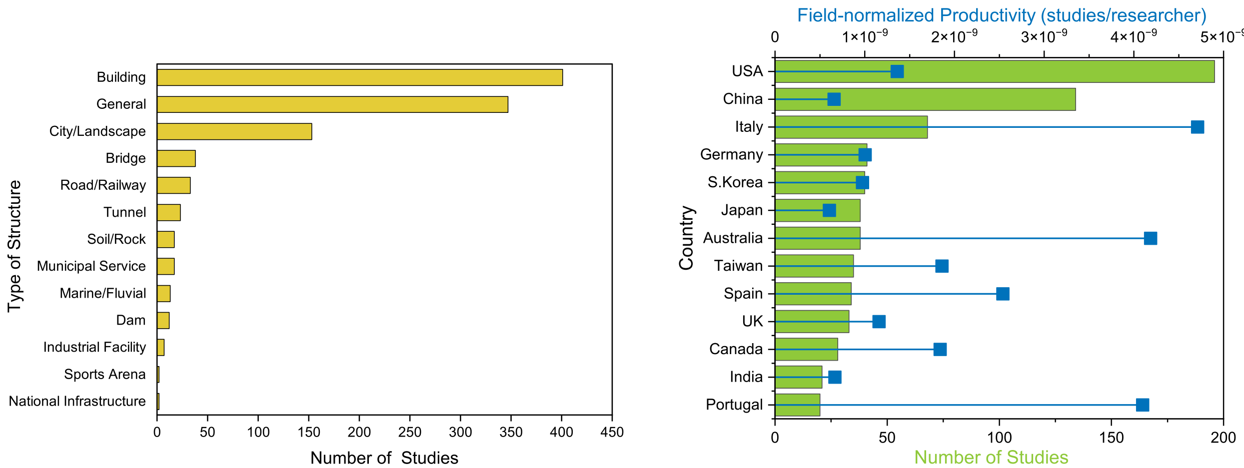
Between 2011–2022 the number of XR in AEC publications has been increasing steadily. A dramatic increase in published studies was observed between 2016 and 2019. However, from 2019 to 2022, the increasing tendency stabilized, maybe due to external factors like the onset of the COVID-19 pandemic in early 2020 (Figure 3.16 (a)).

During the analyzed period, the number of studies published for each AEC area (architecture, engineering, and construction) had a very similar evolution (Figure 3.16 (b)). The three areas also interchangeably had the most and least studies in different years. This proximity between the number of studies shows how the XR research interest has been increasing at approximately the same rate in the three areas.

Regarding the physical referent addressed, there was a noticeable prevalence in studies concerning the application of XR in buildings. This prevalence is understandable, as building design, construction, maintenance, and demolition are carried out at a massive rate worldwide. Moreover, apart from studies not focusing on a particular type of physical referent, buildings were followed by urban landscapes as the targeted physical referent in the addressed XR in AEC studies (Figure 3.17 (a)).

Similarly, most of the studies highlighted in Section 3.1 has buildings as physical referents ([11], [72], [113], [150], [153], [182]). Indeed, engineering and architectural design and construction inspection studies focused heavily on the specific design and inspection of buildings.

Regarding the geographical distribution of studies, the USA and China produced the



(a) Physical referent addressed in the analyzed studies. The 'General' type concerns studies that do not focus on a specific structure. [161].

(b) Geographical distribution of primary studies for the 20% countries with the most studies (green) together with *field-normalized productivity* for that country (blue) [161].

Figure 3.17: Types of physical referents addressed in the analyzed studies and geographical distribution of primary studies, together with *field-normalized productivity* [161].

highest absolute number of studies on XR in AEC. They were followed by Italy, which also had the highest number of studies in relation to its research population (*Field-normalized Productivity*[1]), followed by Australia and Portugal (Figure 3.17 (b)).

Regarding the type of display/device addressed in the studies, there was a noticeable increase over the last decade of XR HMDs. In the same period, the number of studies addressing the use of 2D screens decreased significantly (Figure 3.18 (a)). Moreover, in the analyzed period, we can also observe that the reported limitations and challenges related to equipment and software had a decreasing tendency (Figure 3.18 (b)). These results may be a reflection of the substantial leap in XR headsets reliability and performance as well as XR Software Development Kits (SDKs) simplicity over the last decade.

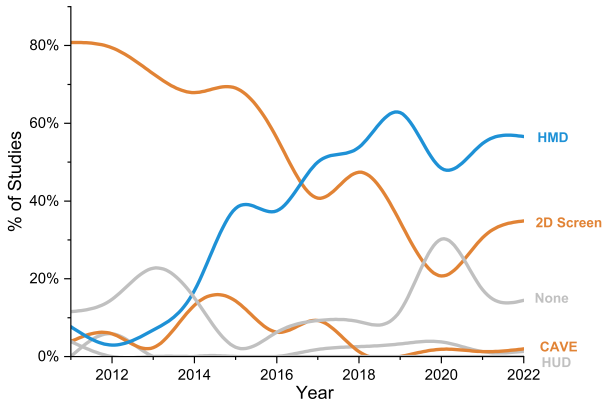
This increasing preference for HMDs over 2D screens for XR applications to AEC was also observed in the studies presented in Section 3.1. Indeed, XR headsets were used in almost all circumstances and types of application, from design to inspection and construction assistance. They were also preferred across studies addressing different modalities, including

[1]This metric measures the number of XR in AEC studies produced by a country per researcher in that country while taking into account the global average of publications per researcher in all fields. It was calculated using the following expression:

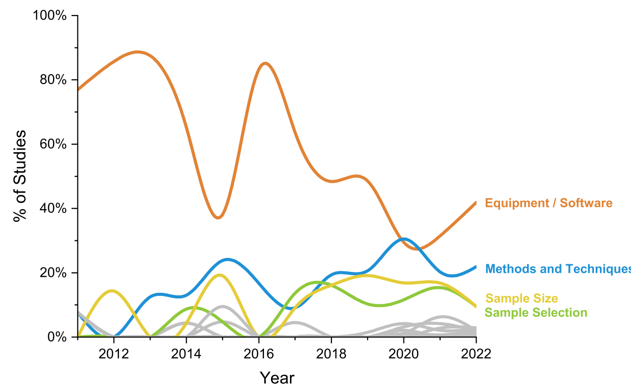
$$Field\text{-}normalized\ Productivity = \frac{Studies_{country}}{Researchers_{country}} * \frac{Studies_{total}}{Researchers_{total}} \qquad (studies/researcher)$$

$Studies_{country}$ - Number of XR in AEC studies indexed by Scopus (2011-2022) produced by each country (affiliation of first author); $Studies_{total}$ - Number of XR in AEC studies indexed by Scopus (2011-2022) across all countries; $Researchers_{country}$ - Number of researchers (of all scientific fields) in each country [179], [180]; $Researchers_{total}$ - Number of researchers (of all scientific fields) across all countries;

AR and VR (*e.g.*, [10], [11], [21], [50], [69], [72], [91], [109], [113], [135], [143], [150], [153]).



(a) Evolution (percentage) of the type of display addressed in studies [161].



(b) Evolution of limitations and challenges cited in the analyzed studies [161].

Figure 3.18: Tendencies registered in the last decade concerning the type of display (a) and type limitations and challenges cited in the analyzed studies [161].

Moreover, later, in 2024/25, we made an updated bibliometric analysis explicitly focused on XR in SHM [160]. It entailed 44 relevant primary studies and included, among other assessments, an author's keyword density and relationship analysis (Figure 3.19). The results showed many studies addressing the application of AR in crack detection. Concurrently, many of these studies also addressed BIM and the use of UAVs.

Information visualization was the most addressed scope in studies focusing on VR. VR-focused studies also addressed frequently 3D modeling from point clouds. It is also possible to identify the tendency for VR-focused studies to address SHM in the context of historic buildings. Furthermore, AR was the most mentioned of the XR modalities, which may be indicative of a strong on-site component in XR in SHM research. It was followed by the VR and MR modalities.

This preference for AR can also be observed in the studies categories described in Section 3.1. Indeed, almost all studies addressing construction inspection, management, and assistance ([6], [50], [91], [109], [135], [153]) also used AR as the preferred XR modality.

By contrast, Section 3.1 studies focused on engineering and architectural design([11], [61], [72], [113], [150], [182]), addressed the use of VR. Conversely, studies addressing construction safety training ([21], [69]) used alternately AR and VR.

Observing Figure 3.17 (a), we can see that scientific studies addressing immersive visualization for dams are still significantly smaller in number than those dedicated to other types of physical referents, like buildings. This smaller number of XR studies addressing dam engineering, compared to other areas, may be related to the increased challenges dams pose (like the physical features of dams and other characteristics already mentioned above).

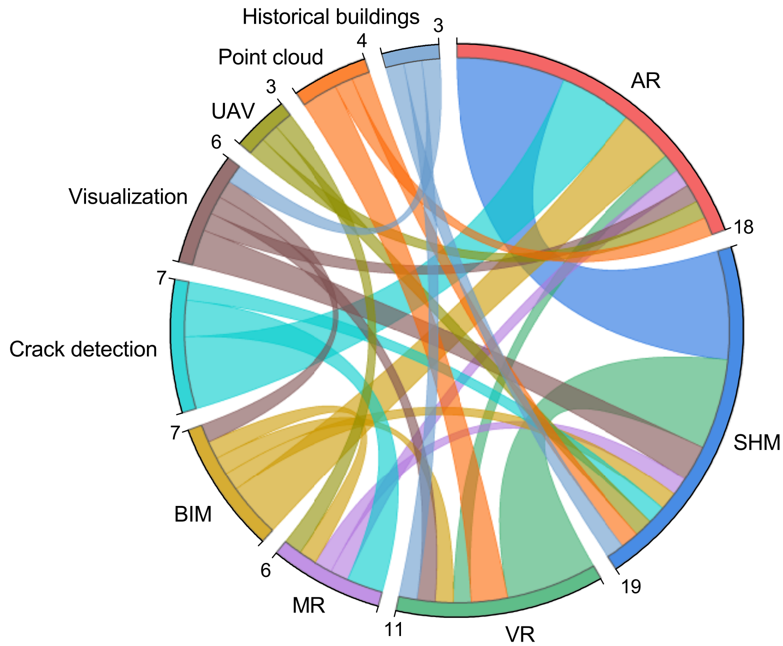


Figure 3.19: Relations between the top 10 most used author's keywords in the analyzed XR in SHM studies. [160].

Section 3.2 addresses some of those studies. Moreover, one of the main examined aspects was transforming engineering and design documentation, including technical design models and BIM data, into 3D assets that can be directly used in XR environments [88], [170], [184]. The effectiveness and efficiency of this transformation are fundamental for streamlining the development of XR applications for dam engineering (and XR engineering applications in general).

While BIM methods have somehow standardized how the different project elements are represented, integrated, and stored, their transformation into usable assets is still complex. It involves heavy preprocessing due to the typically high geometrical detail of engineering BIM and Computer-aided Design (CAD) models. Such high-poly count models have to be simplified for smooth real-time rendering in immersive environments. However, this simplification has to be carried out without losing embed critical information, namely in what concerns design accuracy. Dam engineering models also typically contain rich metadata (materials, annotations, and other technical specifications), which must be retained in order for the XR environment' elements to be actionable, namely in XR dam data analysis applications.

One other aspect that was addressed in the studies presented in Section 3.2 was the use of XR for monitoring dams in the construction stage [90], [133], [169], [187]. Researchers have focused on using AR for that purpose. This XR modality allows the superimposition of digital information concerning what was designed with what was actually built in the real world. In that scope, inspectors wearing AR headsets are offered a relevant resource for supporting the identification, *on-site*, of positional and geometrical discrepancies during and after the construction process.

As we have seen with some of the addressed studies, dam monitoring applications can superimpose relevant information on construction work other than design data. Examples of such information are the movement paths of crane buckets to reduce operational costs [169] or the levels of soil compaction resulting from the operation of roller machines in earth and rockfill dam construction [90].

Some of the analyzed studies are also concerned with using immersive environments to promote public awareness of the hydrological importance of dams and outreach initiatives regarding dam safety control activities. In those scopes, XR technology can be used to simulate the effects of dam failures [151], flood impact [96] or the construction of dams [74] by providing immersive and realistic environments capable of effectively engaging both the general public and policymakers.

Despite being scarce, there are some examples of virtual environments being used in the context of *off-site* dam data visualization. However, they have been developed either primarily for desktop environments [171], not taking advantage of XR headsets' virtues on spatial perception (as addressed in Chapter 2) or for small-scale dam installations [59].

In Section 3.3, we addressed previous scientific work concerning situated visualization and analysis in many domains. Situated visualization and analysis have been applied to such varied areas as improving users' shopping experience [1], [41], agricultural activity [186] and sports [89], among many others.

Likewise, situated visualization can also be very useful in the AEC area, as exemplified in the early example provided by the work of Behzadan and Kamat [12]. The operational advantages they demonstrated by superimposing relevant information to urban pavements, using AR, can be extrapolated to many other AEC domains and types of physical referents, such as buildings, bridges, or dams (and, of course, to other domains outside AEC).

They address the application of AR in the superimposition of virtual elements representing the geometry of municipal underground infrastructure to the pavement of urban streets. Such a mechanism allows municipal workers to visualize how underground utility lines are distributed along sidewalks and roads before initiating underground repair works and excavating the pavement. Such a system provides a practical way to situate municipal infrastructure data. By directly contextualizing data over the object of analysis, the system avoids manually establishing the correspondence between utility blueprints and the urban setting.

Some of the works, however, addressed general purpose situated analytics interaction and visualization techniques for better scoping of data within the object of analysis [40], [41], [42], [43]. These techniques are crucial for better determining how and where data is embedded in the physical environment. They also facilitate the connection between the physical space and the information being conveyed to the user regarding that same space.

In that scope, distinct levels of spatial indirection in data were addressed. For example, in the work proposed by Buschel *et al.* [19] or Guarese *et al.* [60], the data representation is carried out with direct overlay to the spaces and surfaces it concerns. Such configuration corresponds to a lower level of data indirection, as defined in Section 2.3. On the contrary, *e.g.,* Ens and Irani [47] propose using virtual floating windows/panels to represent data. This representation is carried out on-site but presupposes that data is at a certain (conceptual) distance from the object of analysis. Therefore, such configuration corresponds to a higher level of data indirection.

Some of the addressed studies also focus on less conventional techniques for situated visualization. An example is the work proposed by Berger [14], which uses an audiovisual approach for conveying spatial data. Instead of limiting the data display to visual representations, they added an audio layer to improve data spatial perception.

In Section 3.4, we addressed existent scientific work concerning a particular subset of situated visualization - proxsituated visualization - that uses representations of the referent instead of the actual physical referent.

There are a couple of considerations we should take into account when looking at these studies. The first is that while proxsituated representations are typically associated with a virtual referent, that does not mean that proxsituated applications have to use VR necessarily. Moreover, as we have seen in Section 2.3 and some of the analyzed works [24], [101], [102], [103] proxsituated analytics allows users to go beyond the egocentric point of view (typically found in immediate situated analytics).

One other consideration is the data representation level of spatial indirection. Data spatial indirection is a determining factor in how we convey the data to the user. In some of the addressed related work [131], [172], different levels of data spatial indirection were addressed. In that scope, Weidinger *et al.* [172] found that users considered a low level of data indirection helpful in understanding differences. However, they preferred simultaneous viewing of data representations with both lower and higher levels of data indirection.

In that scope, Ready *et al.* [131] addressed the use of different data indirection levels depending on the data hierarchy level being visualized. Indeed, the proxsituated environment that they presented uses primarily 3D bars, representing water different water properties, overlaid directly on the referent (lower data indirection). However, when the user selects a specific bar, a floating panel with a 2D line chart representing the evolution of recorded values over time is displayed (higher data indirection).

Chapter 4

Exploring Situated Analytics in Dam Safety Control

In this chapter, we describe the exploratory process carried out during the development of this dissertation. We address a series of aspects related to situated analytics that were covered in the scope of dam safety control. The following sections outline how we explored the different components of situated analytics, such as the immediate and proxied approaches, the particularities of distinct XR devices, the levels of data indirection, or the levels of visual detail. This work was carried out in close collaboration with dam specialists from CDD at LNEC.

4.1 Immediate Situated Approach

Our work in immersive data analytics in dam safety control began with exploring the use of XR for *on-site* structural data visualization. This first project began when the author was completing his master's thesis (late 2018) and continued through the early stages of his PhD (2020).

We focused on exploring how AR-powered touch devices, like tablets or smartphones, could be used for visualizing the networks of sensors inside and on the dam's surface. In the scope of this exploration, we set to develop a prototype whose effectiveness could be tested in the field.

For this work and most of the subsequent work addressed in this dissertation, we used the *Cabril Dam* as a case study. This dam is a structure that has been highly studied by engineers and civil/dam engineering researchers. As such, it was the structure that the specialists at CDD at LNEC advised we use for validating our prototypes. The *Cabril Dam* is a double curvature concrete arch dam built in 1953. It is located in the *Zêzere* river, on the border between the counties of *Pedrógão Grande* and *Sertã*. The structure has a crest length of 290 m, and the central console thickness varies between 4.5 and 19 m [120]. It is the highest arch dam in Portugal, with a height of 132 m [119] (Figure 4.1).

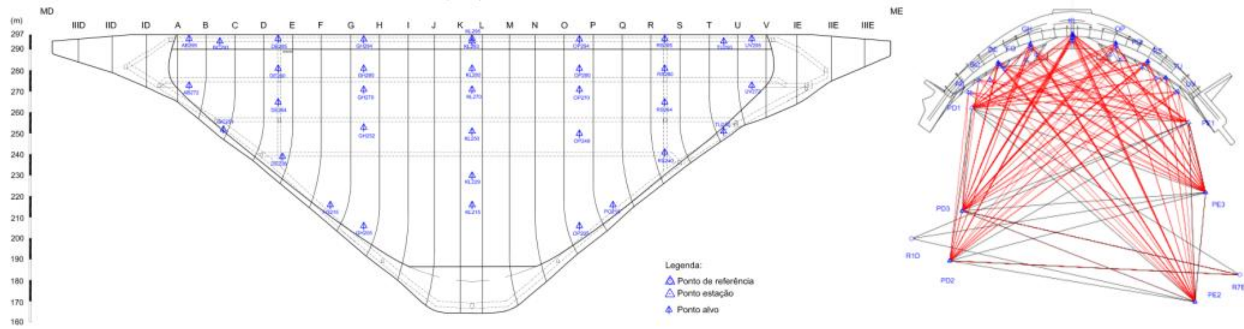
Figure 4.1: General view of the Cabril Dam (left) and side view of the downstream face of the structure(right) [162], [163].

The *Cabril Dam* includes several sensors inside its structure. It also incorporates other devices, like geodetic marks on the dam's downstream face. Dam sensors are used for monitoring many different parameters, including structural displacements [120]. Structural displacements are movements or shifts that occur in the structure over time. They depend, among other factors, largely on the hydrostatic pressure of the reservoir water. So, throughout the year, as the reservoir water level changes, so will the displacements.

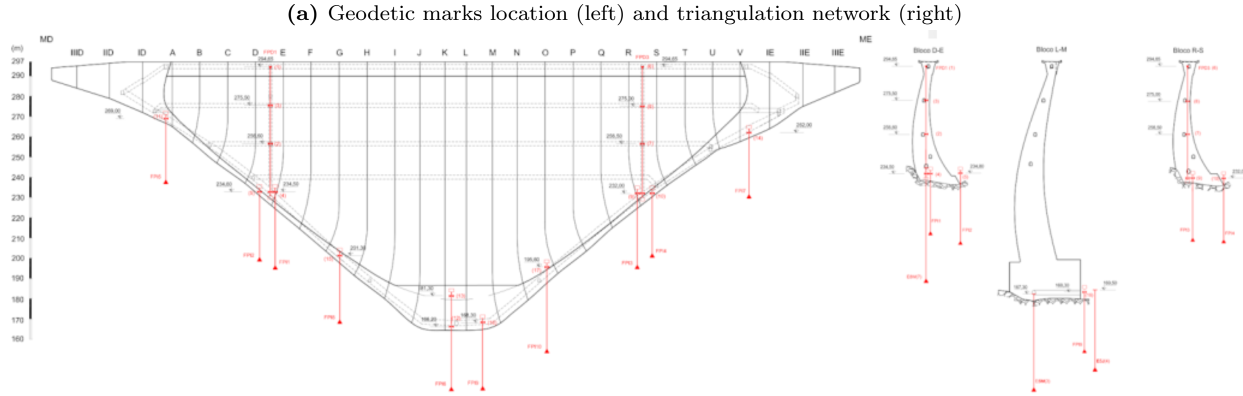
The monitoring of horizontal displacements in the structure, which was the specific focus of this work, is carried out in the*Cabril Dam* mainly through three processes [120]:

- Using geodetic methods, through exterior triangulation of a network of fixed marks installed in the downstream face of the dam (Figure 4.2 (a));
- Through 10 plumb lines installed in vertical holes in the interior of the dam structure (Figure 4.2 (b));
- Using GNSS equipment installed in the central point of the top of the dam and the outskirts of the dam.

So, the prototype we wanted to implement would allow the superimposition of the positioning and geometry of the network of sensors to the user's view of the real world. It would also enable the visualization of displacements measured in those sensors. This system would



(a) Geodetic marks location (left) and triangulation network (right)



(b) Plumblines location

Figure 4.2: Location of different types of sensors in the interior of the *Cabril Dam* (LNEC [120]).

offer engineers and field technicians a better perception of the distribution of the monitoring device networks during periodic inspection visits.

With this objective in mind, we selected *Android* tablets as the target hardware platform. We chose this platform mainly due to the following reasons: cost-effectiveness, higher battery life, and better environmental resistance (durability) when compared to dedicated AR headsets like *Microsoft Hololens*. We also chose *Unity* as a graphical engine due to its simplicity, performance, and overall hardware compatibility. For the AR SDK, we opted for *Vuforia* due to its native integration with Unity, and good performance in exterior environments, as highlighted by Marto *et al.* [105].

For superimposing the relevant virtual elements of our application to the actual dam, we needed accurate AR tracking. Due to our structure's sheer size, the use of fiducial markers would not be feasible, let alone practical. Therefore, we had to opt for a marker-less tracking solution.

Within that scope, we used *Vuforias' Image Targets* tracking technique. This technique uses pre-captured 'target' photos of the environment we want to augment. The AR SDK will then estimate the approximate position and orientation of the camera in relation to the target by identifying key features of those photos.

When compared with other AR tracking techniques, the use of *Image Targets* is less sensitive to changes in luminosity, according to Marto *et al.* [105], making it more appropriate for outside environments.

However, even if these were the most suitable techniques for our case, effectively tracking such an immense structure like the *Cabril Dam* was a massive challenge. Concrete arch dams are monolithic structures with mostly regular monochrome surfaces and few distinctive features.

The solution to a seemingly insoluble problem was to use the facade features of the powerplant building located at the base of the dam. However, this solution was not without problems, mainly due to the buildings' facade being located at a considerable distance (45 m) from the dam's downstream face. This difference between the tracked surface (the buildings' facade) and the target object (the face of the dam) later resulted in some loss of accuracy in virtual object representation due to the parallax effect it created.

To increase the probability of image target detection and improve tracking stability, we used multiple image targets focusing on distinct architectural features of the building's facades. For each architectural feature, we also made multiple image targets throughout the day, during field visits (Figure 2.2, left) so target detection and tracking would be possible with distinct levels of luminosity and shadows (Figure 4.3).

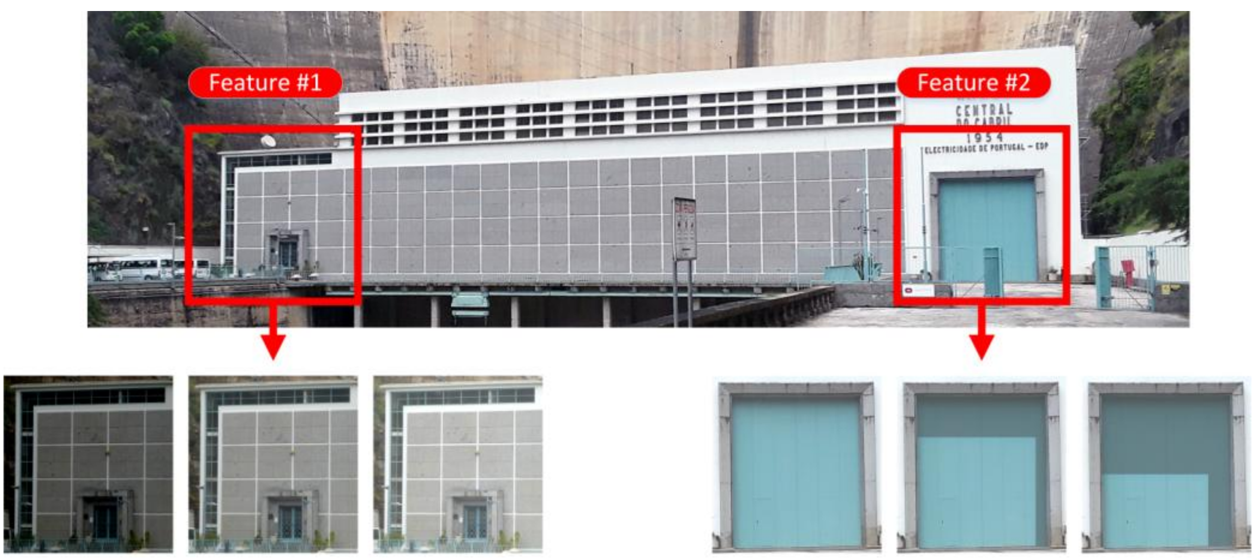


Figure 4.3: Examples of architectural features that were used as image targets. Multiple versions of these features were used with different levels of luminosity and shadow coverage [162], [163].

Using the prototype (we named *DamAR*) is as simple as pointing the tablet camera to the dam, and the sensor networks will be overlaid to the video passthrough of the structure and displayed in the tablets' screen (Figure 4.4). During technical visits to the site, a relatively stable operation of the system was achieved at a distance of up to 110-130 meters from the facade of the powerplant (155-175 meters from the dam downstream face) (Figure 4.5).

Figure 4.4: Network of sensors overlaid to the *Cabril Dam* structure using *DamAR* [162], [163].

Figure 4.5: During technical visits to the site, a fairly stable operation of the system was achieved at a distance of up to 110-130 meters from the facade of the powerplant (155-175 meters from the dam downstream face) [162], [163].

DamAR 's User Interface (UI) allows users, through an AR layers menu, to select which type of sensor they want to see represented over the dam (plumblines, geodetic marks, and GNSS). They can select (touch) a specific area of the dam in the tablet to see a zoomed-in image of the structure, where they can then select a specific sensor that they want to know more information about (Figure 4.6 (a)). The selection of a specific sensor transitions to a full-screen representation of line charts with the evolution of displacements over time. These charts are represented together with the reservoirs' water level and air temperature for the same period (Figure 4.6 (b)). The charts can be panned and zoomed to display specific periods.

(a) The model moves backward to give the illusion to users that they are moving forward

(b) The model moves forward to give the illusion to users that they are moving backward

Figure 4.6: General view of *DamAR* 's UI (a) and full-screen line charts representing horizontal displacements, air temperatures and reservoir water level (b) (*mockups*) [162], [163].

With the *DamAR* project, we first explored how situated environments could be used in data visualization in dam safety control. The prototype corresponds to an immediate situated [138] visualization solution. It is directed at an *on-site* scenario, where the user can observe the physical referent (the actual dam) while using the prototype. Even though it superimposes the sensor's network representation directly over the dam, the actual data (the displacements, water levels, and air temperature) are not represented overlaid to the dam. As such, we can classify data representation as having a high spatial indirection, according to the model proposed by Satriadi *et al.* [138].

Note: The work described in this section was addressed by Verdelho Trindade *et al.* [157], [160], [162], [163], [165].

4.2 ProxSituated Approach

With *DamAR* we explored how XR immediate situated visualizations could be used to support *on-site* dam safety control tasks. However, now we were curious if we could address a similar data visualization use case but this time focusing on *off-site* operation.

With that objective, we set to develop *DamVR* , a VR application that technicians and engineers could use for visualizing the sensor networks and corresponding registered values over time off-site in an immersive environment (Figure 4.7). In that scope, we also wanted to explore and take advantage of the increased immersiveness offered by VR headsets.

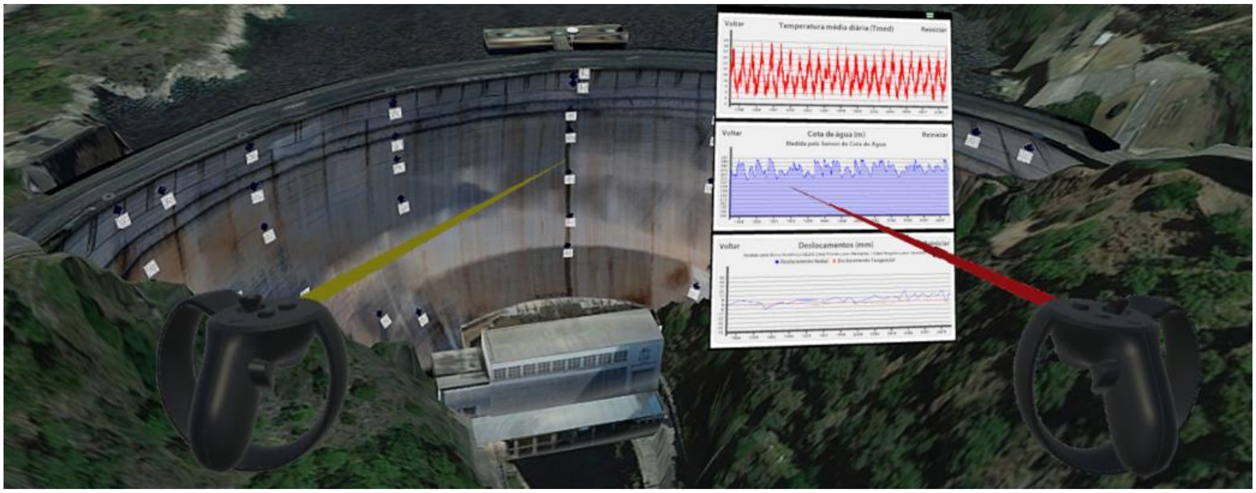


Figure 4.7: Overview of *DamVR* 's virtual environment, including sensor networks and data representation in floating panels (*mockup*) [164].

We knew introducing a headset VR application in the dam safety control field would present significant challenges. Indeed, experts in this field have long relied on traditional desktop PCs with 2D screens for data visualization. A VR approach would involve multiple layers of adoption resistance related to technical, psychological, and practical aspects perceived by the users.

Due to our familiarity with this graphical/game engine, we again opted for *Unity* for supporting the development of our prototype. This graphical engine is also compatible with a wide range of VR headsets, including the hardware platform we selected, the *Oculus Rift*/Meta headsets.

In addition to the interaction in the virtual environment, four main visual components needed to be implemented as part of our prototype development: the dam and surroundings model, a sensor network model, a UI, and the data representation. Developing the dams' model was challenging, as it needed to accurately reproduce the geometry and conditions *in-situ*.

The model of the *Cabril Dam* and surrounding environment is generally made up of three parts: the dam structure, the terrain, and the upstream and downstream water bodies. The model of the dam was executed from a point cloud resulting from 3D laser scanning campaigns at the *Cabril Dam*, commissioned by LNEC.

The acquired point cloud data was processed to remove noise, outliers, and artifacts. The next step consisted of surface reconstruction. With that objective, a mesh of the structure was generated using surface-based methods [15]. The resulting mesh was further refined and optimized using smoothing, decimation, and hole filling. This process allowed us to enhance the quality of the initial mesh representation.

For texturing the model, a set of photographs of the dam, captured with a multi-sensor laser scanner, was used to compile a photo mosaic. The texture coordinates of the mosaic were then mapped to the 3D object through UV mapping using the modeling software *Blender*. The finalized model of the dam structure was exported to the .FBX file type using *Blender* and then imported to *Unity*.

The surrounding terrain was modeled using a similar process. The terrain mesh was created using elevation data. Aerial photographs were then used to build a photo mosaic. This mosaic was mapped to the terrain as a base layer, which ensured the terrain hues were as close to reality as possible (Figure 4.8). On top of this texture, environmental spatial elements, like trees, bushes, and rocks, were added to increase realism.

While the downstream water body was modeled by a static plane, the upstream reservoir water plane was modeled using flat meshes for multiple water levels. As the water level varies up and down, the position of the boundary points between the water mesh and the dams' upstream face is then adapted on runtime using interpolation between the consecutive pre-built meshes. An abstraction mechanism that significantly simplifies this process will be addressed later in Section 5.9.

Concerning the sensor network, at the CDD at LNEC experts' advice, we decided to address five types of sensors. These sensors included geodetic marks, plumblines, GNSS equipment, and leveling marks, all used for registering structural displacements. They also included accelerometers for measuring accelerations and water elevation sensors for registering the upstream reservoir water level. Instead of a more symbolic representation of sensors used in *DamAR* , for the VR prototype, we opted for depicting sensors in a geometrically accurate way.

With *DamVR* 's virtual environment defined, we needed to implement interaction and data visualization. The selection of objects within the immersive environment was implemented with raycasting [55]. Visible beams emanate from the VR controllers, which users can point to select and interact with the environment.

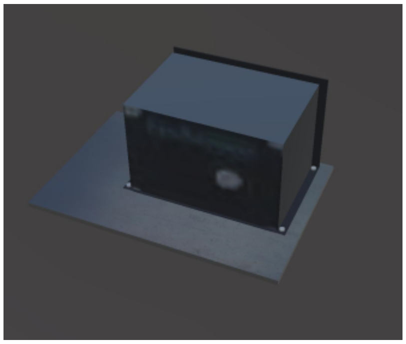
For the locomotion, we opted for controller-based egocentric [34], [51], smooth (continuous) locomotion. We also implemented teleportation-based locomotion using 'point to teleport'.

The users can move freely through the virtual environment and point the controller's beams to a specific sensor to select it. Some of the sensors are located outside the dam's structure and, as such, are always visible. However, other sensors are occluded because they are located inside the dam's structure. These sensors can be visualized by pointing the selection beam at a portion of the structure, which will become semi-transparent, revealing the sensors inside. They can then be selected by pressing the controller trigger button.

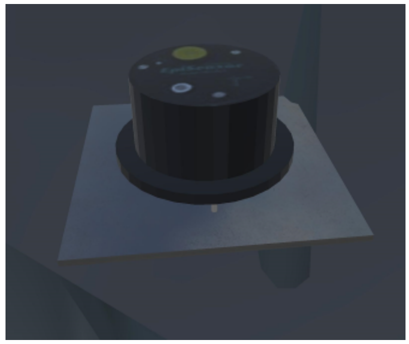
(a) The representation of the terrain in the immediate surroundings of the *Cabril Dam*

(b) An overview of the large-scale terrain (highlighted in orange is the immediate area of the *Cabril Dam*)

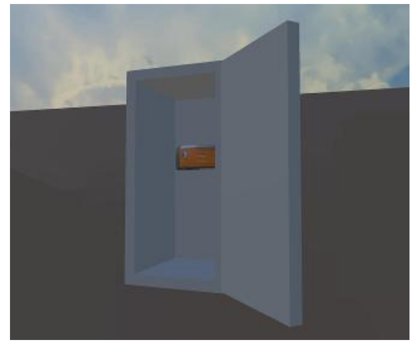
Figure 4.8: Model of the terrain used in *DamVR* [165]).



(a) Uniaxial accelerometer

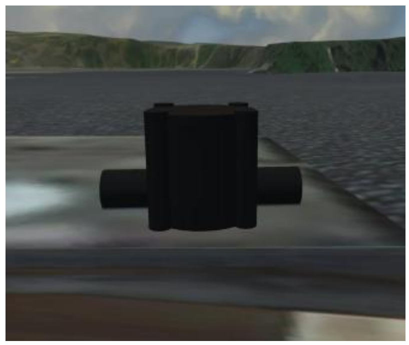


(b) Triaxial accelerometer

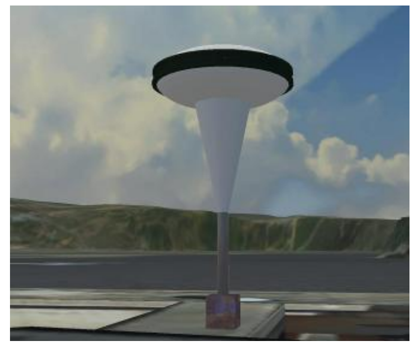


(c) Data acquisition unit

(d) Leveling marks



(e) Water elevation sensors



(f) GNSS

Figure 4.9: Models of different elements of sensor networks [165].

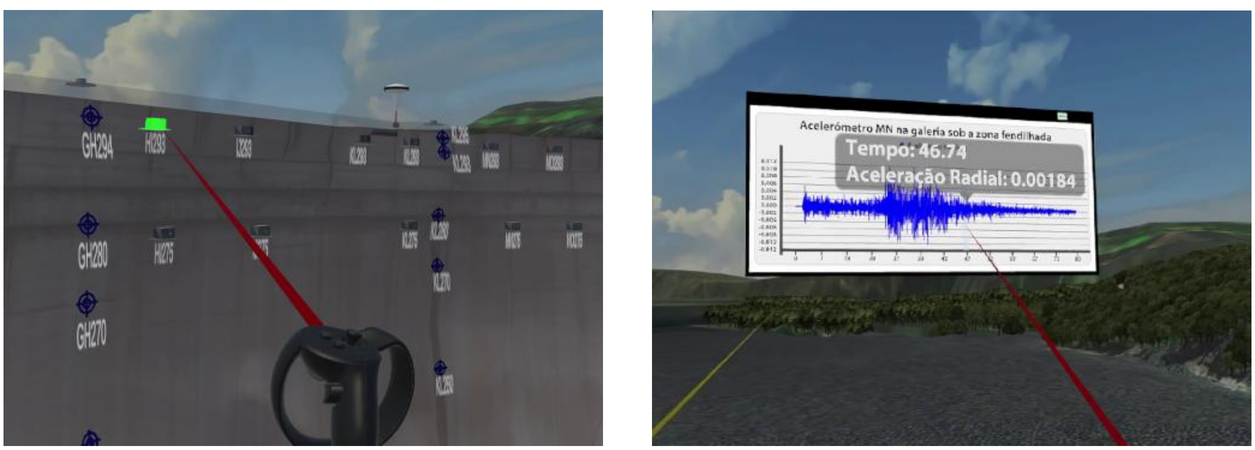
Data visualization is carried out using floating panels, which are shown in the virtual environment when users select the sensors (Figure 4.11 (a)). These panels contain interactive 2D line and area charts representing the several parameters registered in the sensors over time.

For most sensor types (except accelerometers), panels with three distinct yet complementary idioms are shown: a line chart with the radial and tangential displacements, a single area chart with the upstream water level, and a line chart with the evolution of average daily air temperature. For the accelerometers, a single line chart is shown, depicting registered radial, tangential, and vertical accelerations for localized seismic events (Figure 4.11 (b)).

The three idioms, shown for most sensor types, share the same timeline on the horizontal axis, which helps users frame a specific measurement in the scope of a certain water level and air temperature combination. Such correspondence is important for dam engineers to detect abnormal deviations in the dams' behavior. The panel idioms can be panned and zoomed. Moreover, because the timeline of the three idioms is bounded, when users pan or zoom a specific idiom, the same action is automatically reproduced in the other two.

The floating panels can be dragged and dropped in the virtual environment using the

Figure 4.10: An 'X-ray' overview of the networks of sensors located inside the model of the *Cabril Dam* represented in *DamVR* 's virtual environment [164].



(a) Selecting an accelerometer located inside the structure

(b) Navigating the corresponding idiom

Figure 4.11: The users can move freely through the virtual environment and point the controller's beams to a specific sensor to select it (a). Panels containing interactive charts representing the several parameters registered in the sensors over time are then shown (b) [165].

selection beams, maintaining the original distance from the user position. They can also be moved closer or further away from the user by pushing the controller's thumbstick up or down. Furthermore, panels can be scaled by pushing the thumbstick left or right.

DamVR allowed us to go a step further and explore *proxsituated* environments for the first time. While its conception was based on an existing immediate situated visualization use case

(*DamAR*), this *proxsituated* implementation had its own context, challenges, and benefits. *DamVR* is directed at an *off-site* scenario, where the user can observe a representation of the physical referent (instead of the actual dam). This setting provides dam engineers and technicians with a contextualized visualization of dam structural safety data without having to travel to the actual location. Indeed, dams are frequently located in remote locations, often in harsh and difficult-to-access valleys or narrow river gorges.

In the *DamVR* virtual environment, the sensor networks (geodetic marks, plumblines, GNSS equipment, and leveling marks) are represented directly in the dam structure. However, the dam safety control data (displacements, accelerations, air temperatures, and water levels) are not represented overlaid to the dam. Instead, they are shown in traditional 2D charts, represented in panels floating around the user. As such, similar to what happens for *DamAR* , we can classify the representation of data in *DamVR* as having a high spatial indirection, according to the model proposed by Satriadi *et al.* [138].

The proxied referent was modeled with relatively high levels of visual detail using a high polygon count 3D dam model with photographic textures. However, we did not fully explore other aspects of visual detail, such as realistic lighting, advanced shading, atmospheric effects, and other post-processing effects and their impact on user experience.

Note: The work described in this section was addressed by Verdelho Trindade *et al.* [164], [165] and Leitão [83].

4.3 Increasing Visual Detail

In the previously mentioned work, we explored how immediate situated and *proxsituated* approaches could be used for visualizing sensor networks and the associated time-dependent structural datasets contextualized with the dam (or the dam representation).

In the *DamVR* project, we addressed using accurate geometry and photographic textures for the dam and surrounding terrain. And *DamVR* 's virtual environment could indeed reproduce the geometry and conditions found *in-situ*. However it became evident that the experience made it difficult for users to feel as though they were genuinely standing before the dam.

As such, in our next step, we would focus on addressing other factors of visual detail, like realistic lighting and advanced post-processing effects. We wanted to understand the relative impact of these factors on the virtual environment's realism. With that objective, we set to develop a simpler, proof-of-concept prototype that would allow users to visit the *Cabril Dam* structure and surroundings.

With this perspective in mind, we set to implement a photorealistic environment of the *Cabril Dam* (Figure 4.12). We aimed to explore how the application of different techniques and methods could improve the dam safety control virtual environment realism and sense of presence. To achieve the best possible graphic fidelity offered by the graphical engine, we used Unity's High Definition Render Pipeline (HDRP).

Figure 4.12: General view of the photorealistic virtual environment [160].

We first focused on complementing the existing 3D models used in *DamVR* with specific landscape elements. These landscape elements included service buildings located throughout the surroundings of the dam and electrical towers in the downstream area of the dam[1], large trees located near the dam's crest, and a deactivated turbine, also located near the dam's crest, which is a well-known landmark/monument of the *Cabril Dam*. This set of elements contributed to reproducing the ambiance that characterizes the place with greater fidelity.

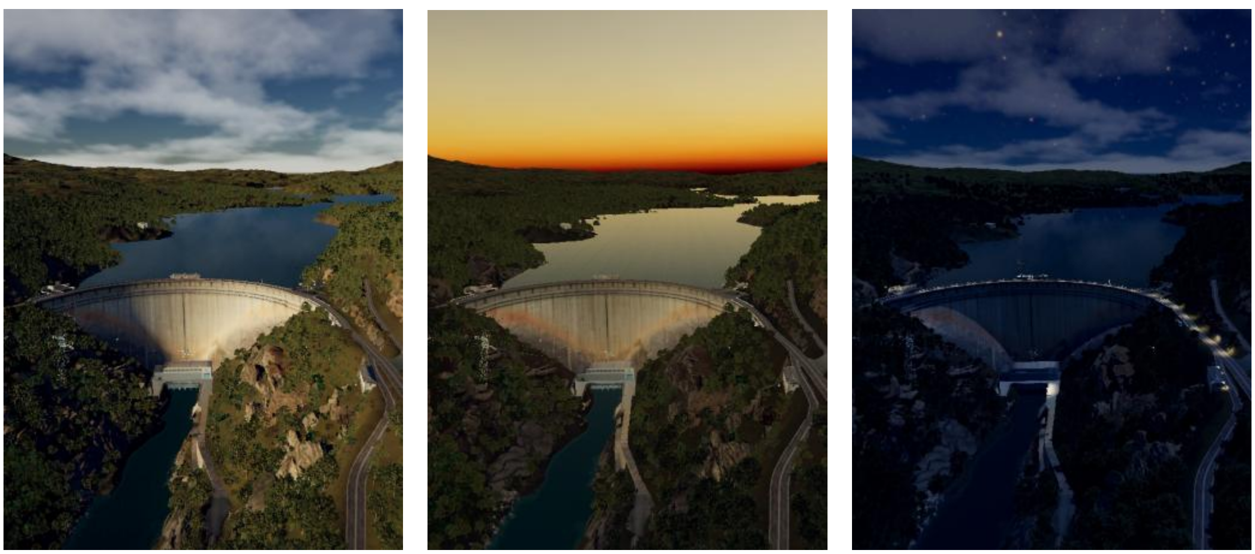
We also wanted the lighting model of the virtual environments to reflect the present time of day and season. We were hoping that this factor would further contribute to improve the sense of presence. With that objective, we implemented a dynamic day-night and seasonal

[1]These electrical towers carry transmission-level power lines used to transport electricity from the power station at the base of the dam to substations.

cycle simulation.

This simulation was implemented primarily by adjusting the position and orientation of directional lights representing the sun and moon [23]. For that purpose, the rotational angles of these two elements vary around the virtual environment's horizon and zenith, reflecting changes in altitude and azimuth, which characterize the present date and time of day.

For increased realism, the day-night and seasonal cycle simulation mechanism was integrated with HDRPs' environmental effects. In particular, we used 'Sky', 'Clouds', and 'Fog' environmental effects. We utilized the volume framework for creating a physically based sky which allows a fine setting a multitude of parameters that affect the sky tone, such as the atmospheres' air density. The light of the sun and moon were configured to affect the physically based sky, which enabled the joint effect of the temporal cycle. Furthermore, to simulate street lighting on the dam, we used spotlights that are only turned on at night (Figure 4.13).



(a) Morning **(b)** Dusk **(c)** Nighttime

Figure 4.13: The day-night and seasonal cycle simulation mechanism [160].

We also used HDRPs' volumetric clouds, which are capable of moving, can render shadows, and receive fog and volumetric light. Likewise, we used the global fog effect, which enables glow and crepuscular rays through clouds and trees.

To further tweak the virtual environment, we configured HDRPs'post processing effects. These effects included, among others, color, depth of field, and bloom adjustments.

Implementing this photorealistic proxituated environment allowed us to explore other facets of visual detail that had not been addressed in the previous works. This environment corresponds to a higher level of visual detail, which is achieved through a broader set of aspects that collectively determine the overall Level of Detail (LOD) and realism. These aspects include 3D models with high polygon count and high-resolution photographic textures. They also include a realistic lighting model with dynamic lighting, provided by the HDRP pipeline tools. Likewise, they include anti-aliasing rendering and post-processing effects. Furthermore, several environmental factors are introduced, such as atmospheric effects.

Note: The work described in this section was addressed by Verdelho Trindade *et al.* [160] and Chin [23].

4.4 Reducing Data Spatial Indirection

During this exploratory journey through situated visualization in dam safety control, we started by addressing an immediate situated solution. We then explored how proxsituated approaches could be applied to *off-site* dam data visualization using a representation of the dam instead of the actual structure. Furthermore, we addressed improving several aspects of visual detail within our virtual environment to provide a more realistic immersive experience, potentially capable of providing a better sense of presence.

As a further exploratory step, we decided to address the use of a distinct level of spatial data indirection compared to the one we had used in our previous work. In particular, we wanted to explore the use of low levels of spatial indirection in a proxsituated analysis environment.

With that objective in mind, we set to develop a prototype that would allow data representation directly over the physical referents' model. In that scope, we opted, at the advice of CDD at LNEC experts, to focus on two types of data representations. The first would be the deformation of dam structures due to the action of hydrostatic pressure. The second would be the visualization of distinct modes of structural vibration [75].

The resulting VR proxsituated prototype, named *ImmersivizDam* , was built upon the lessons learned from the previous projects. It is directed at the *off-site* visualization of structural data, with low spatial indirection, directly superimposed to the *Cabril Dam* representation.

The prototype uses runtime-generated meshes built from external .CSV files containing a simplified version of the dams' geometry (used by CDD at LNEC in structural behavior prediction models) and discrete structural displacements data corresponding to distinct upstream reservoir water levels. These meshes enable the depiction of 3D idioms representing the dam's deformed configuration, together with superimposed spatial heatmaps representing displacement magnitudes (Figure 4.14).

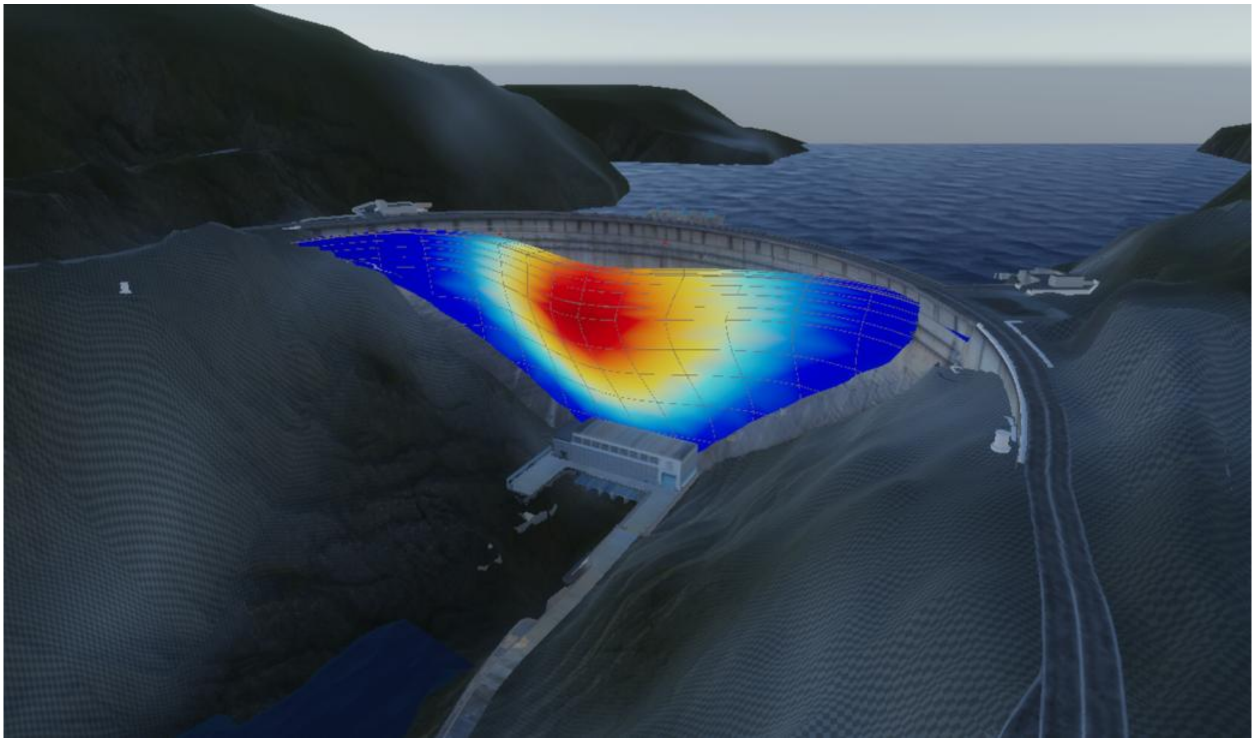


Figure 4.14: Spatial representation of the dam deformed configuration with a heat map representing the distribution of theoretical models' predicted displacements for a specific upstream reservoir water level [160].

As users change the current water level in the UI menus, the mesh is recalculated to reflect the dam's deformed configuration that results from the hydrostatic pressures that occur for that specific water level. Processing this variation in the meshes' geometry at runtime consists of repositioning each key vertex of the undeformed mesh to reflect the new displacement values resulting from a specific water level. A custom shader is then used to apply the displacement heatmap over the deformed mesh.

In addition to changing the water level, the UI also includes an option for increasing/decreasing the scale factor of the structural displacement representation. This option enables users to configure the radial magnitude with which the deformed configuration of the dam will be represented in the virtual environment.

Another type of structural data representation that the prototype supports is the animated simulation of the modes of vibration of the dam. Users can pause and restart the animation within the UI. They can also alternate between three modes of vibration, corresponding to distinct frequencies [75] and upstream water levels (Figure 4.15).

The prototype also includes specialized analysis features, made possible by the versatility offered by the fully programmatic rendering of meshes representing the deformed configurations of the structure at runtime. These analysis features consist of spatial segmentation of structural data. This segmentation results in idioms being represented solely on specific

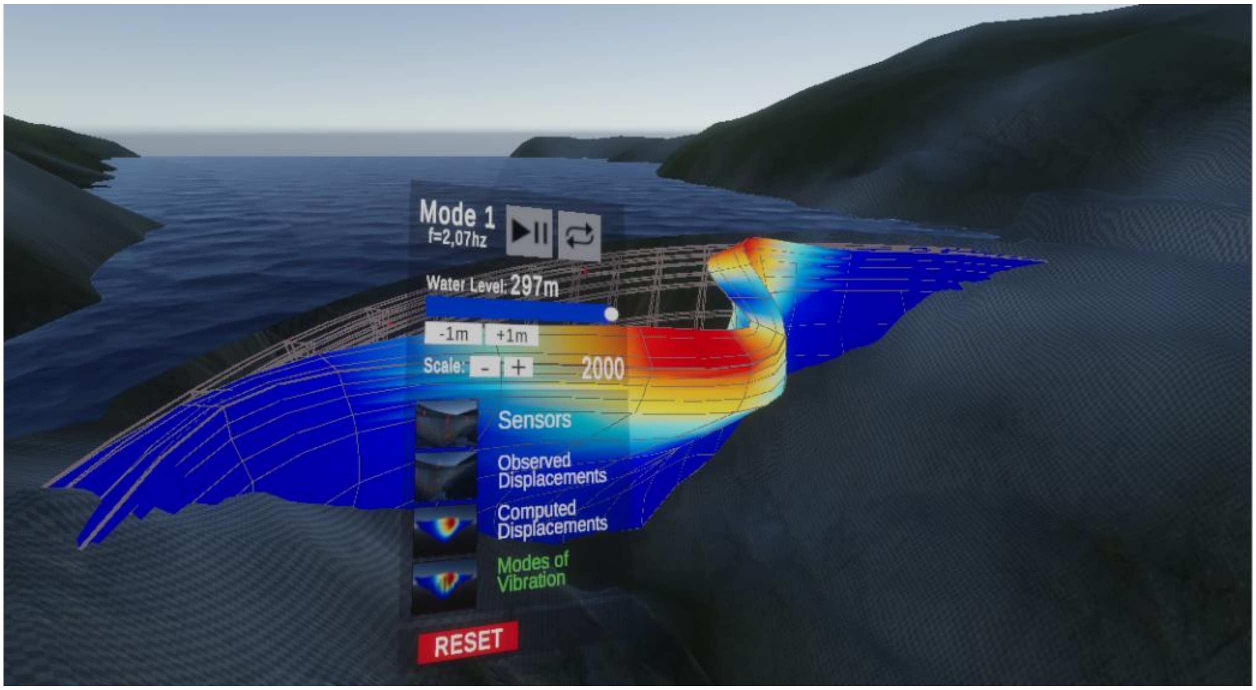
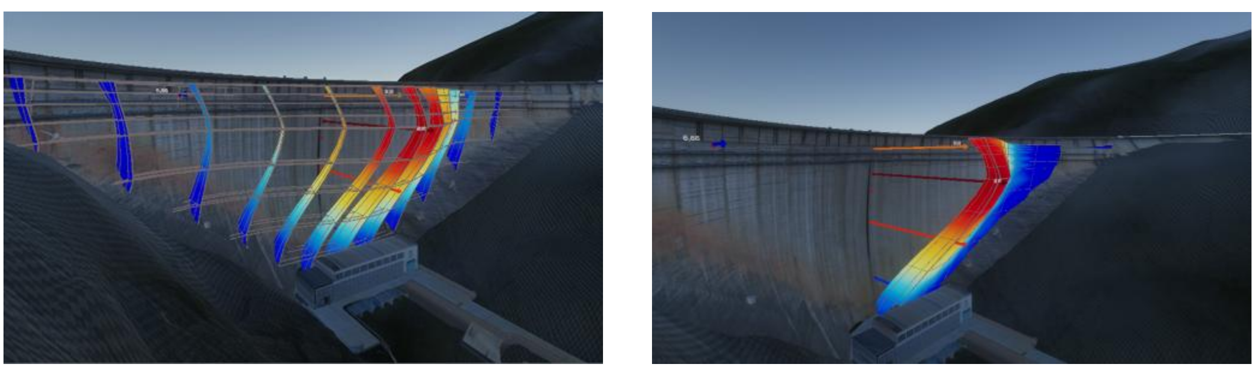


Figure 4.15: Modes of vibration simulation and *ImmersivizDam* UI [160].

portions of the structure, like the structural joints or central console (Figure 4.16 (a)). The resulting visualizations are very useful for dam engineers to better understand the individual behavior of specific structural components.

In addition, the prototype also supports the combined representation of continuous segmented meshes corresponding to calculated/theoretical displacements together with a discrete representation of observed displacements using vectors (Figure 4.16 (b)).



(a) **(b)**

Figure 4.16: Two examples of segmentation of data idioms for analyzing structural behavior at specific components of dams. An isolated visualization of the deformed configuration and theoretical displacements heat map at the dams' construction joints (a). Combined visualization of a continuous segmented representation of theoretical displacements together with a discrete representation of observed displacements (using vectors) at the central console (b) [160].

The *ImmersivizDam* proxsituated environment allowed us to explore the representation of structural data with low spatial indirection. It also introduced specialized analytics features that consisted of spatial segmentation of structural data idioms. Furthermore, the prototype used a higher referent visual detail. However, unlike the previously explored proxsituated solutions, it corresponds to a lower level of visual detail for the environment surrounding the referent.

Note: The work described in this section was addressed by Verdelho Trindade *et al.* [160] and Sequeira [144].

Chapter 5

DamXR: A Framework for ProxSituated Dam Visualization

The incremental work discussed in the previous section culminated in the development of a solution that would bring together the main aspects addressed into a single framework. This framework, named *DamXR*, was used for developing a displacements visualization application, built to support a user study for answering the research questions of our thesis. The *DamXR* XR *proxsituated* visualization framework can facilitate and be the basis for future dam safety control analysis applications.

In the context of supporting the user study, the framework was applied in a use case consisting of dam structural data visualization framed within the dam structure. As we did for the work addressed in Chapter 4, due to our familiarity with the *Cabril Dam*, and the fact that this is a widely studied structure, with full structural sensor instrumentation, our proof-of-concept case would also be in the context of this dam.

In particular, this first application of the *DamXR* framework would be carried out in the scope of structural displacements visualization registered over time. These time-dependent datasets include displacements measured in geodetic marks along the downstream face of the *Cabril Dam*. The application would also include numerical displacements calculated using finite elements prediction models for those same mark positions (Figure 5.1).

The effective analysis of such data is fundamental for dam specialists to understand how the dam behavior is evolving over time. Likewise, the comparison of how the numerical finite elements models predicted the dam was going to behave, with the behavior that the dam actual had, enables specialists to detect possible structural safety risks.

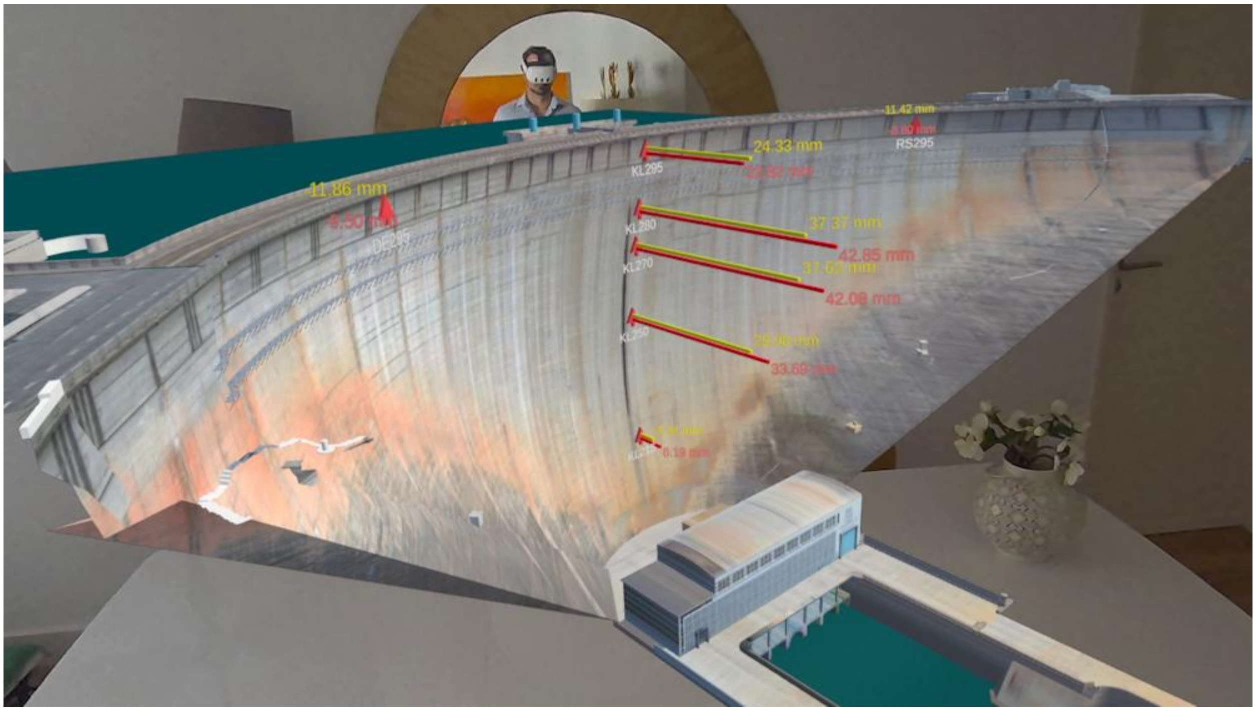


Figure 5.1: The *DamXR proxsituated* environment with the displacements visualization feature/application built upon the *DamXR* framework.

5.1 Requirements

Given the complexity of developing such a system, we wanted to carefully consider the main requirements that would allow it to fulfill the proposed objectives. These requirements were established based on the lessons learned from our previous work. In that scope, we also identified the aspects whose abstraction would yield the most significant advantages for the development of future applications.

One of the most relevant aspects that the framework should offer was the ability to enable applications to function seamlessly across desktop PCs, AR, and VR while maintaining the same UI. This aspect is important for two reasons. First, it would allow participants to carry out tasks across different visualization modalities during the user study. Second, it would enable applications to offer users the flexibility to choose the most suitable device and visualization mode for each specific moment of their dam safety control-related activity.

Additionally, by supporting the more traditional desktop mode and visualization technologies like AR and VR, applications developed with the framework would allow a seamless transition between these modalities. This possibility promotes a smoother adoption of XR technologies by users more familiar with conventional computing environments.

Below, we detail the functional and non-functional requirements for the base framework and the structural data visualization feature.

The following functional requirements were identified for the framework:

- Environment rendering and navigation: The system should support model and user interface rendering as well as user interaction, including navigation through the environment.
- XR multi-modal support: The system should run and allow seamless switching between AR (passthrough) and VR modes (full immersion).
- Desktop computer support: The system should run on PCs.
- Visual detail control: The system should be able to switch between rendering objects with photographic textures (higher visual detail) and without textures (lower visual detail).
- Provide a reusable UI component library: This library should include forms, labels, buttons, switches, radio buttons, sliders, picture boxes, and numeric up-down.
- File handling: The system should include file opening, saving, and data parsing mechanisms.
- Support the .FBX and .OBJ file formats for importing 3D models on runtime;
- Support the .XML file format for importing settings and object placement coordinates;
- Support the *MetaQuest* XR headset model family;

The following non-functional requirements were also considered for the framework:

- Single cross-platform codebase: The system code should have a single codebase that supports the following hardware platforms: XR headsets and desktop computers.
- Platform detection and adaptive interface: The system should include mechanisms to automatically detect the running environment and adjust its behavior and interface accordingly.
- Support for adding new dam environments: The system should support integrating and visualizing diverse dam models and other environment features (*e.g.,* water bodies, terrain).

- Unified 3D model usage across modes: The system should employ a single 3D model base (*i.e.*, dam structure, water bodies, and other surrounding features) that is consistently used across all operational modes (AR, VR and desktop).

- Standalone operation on XR headsets: The system should operate autonomously on XR hardware without requiring a connection to an external computer.

- Standalone operation on desktop computers: The system should be self-contained without users needing to install additional software or dependencies on *Windows*-based operating systems.

The following functional requirements were identified for the structural data visualization feature:

- Structural displacements representation: The system should be able to represent 3D and 2D idioms in the environment based on external time-dependent structural displacements datasets files.

- Use .CSV file format for importing displacements datasets: CDD at LNEC uses this file format for outputting data from *Gestbarragens* and other in-house developed software;

- Data representation spatial indirection control: The system should allow switching between representing data overlaid to the referent (lower spatial indirection) and data in panels (higher spatial indirection).

- Support for adding new dam datasets and models: The system should support integrating and visualizing diverse dam models and sensor/mark geometry and displacements datasets.

The following non-functional requirements were also considered for the structural data visualization feature:

- Easy to use: The system should be easy to learn and use;

- Fluid experience: The system should have a consistent frame rate ($\geq$ 90 fps) for both *Meta Quest 3* headsets and *VR-ready* desktop computers to ensure a smooth user experience;

5.2 Approach Overview

With the main requirements established, we set to implement the *DamXR* framework, which would serve as a base for developing XR dam safety control applications. The framework's objective was to offer a set of base modules extending across multiple functional layers to support the implementation of dam safety control features. The architecture of the framework and the displacements visualization feature is illustrated in Figure 5.2.

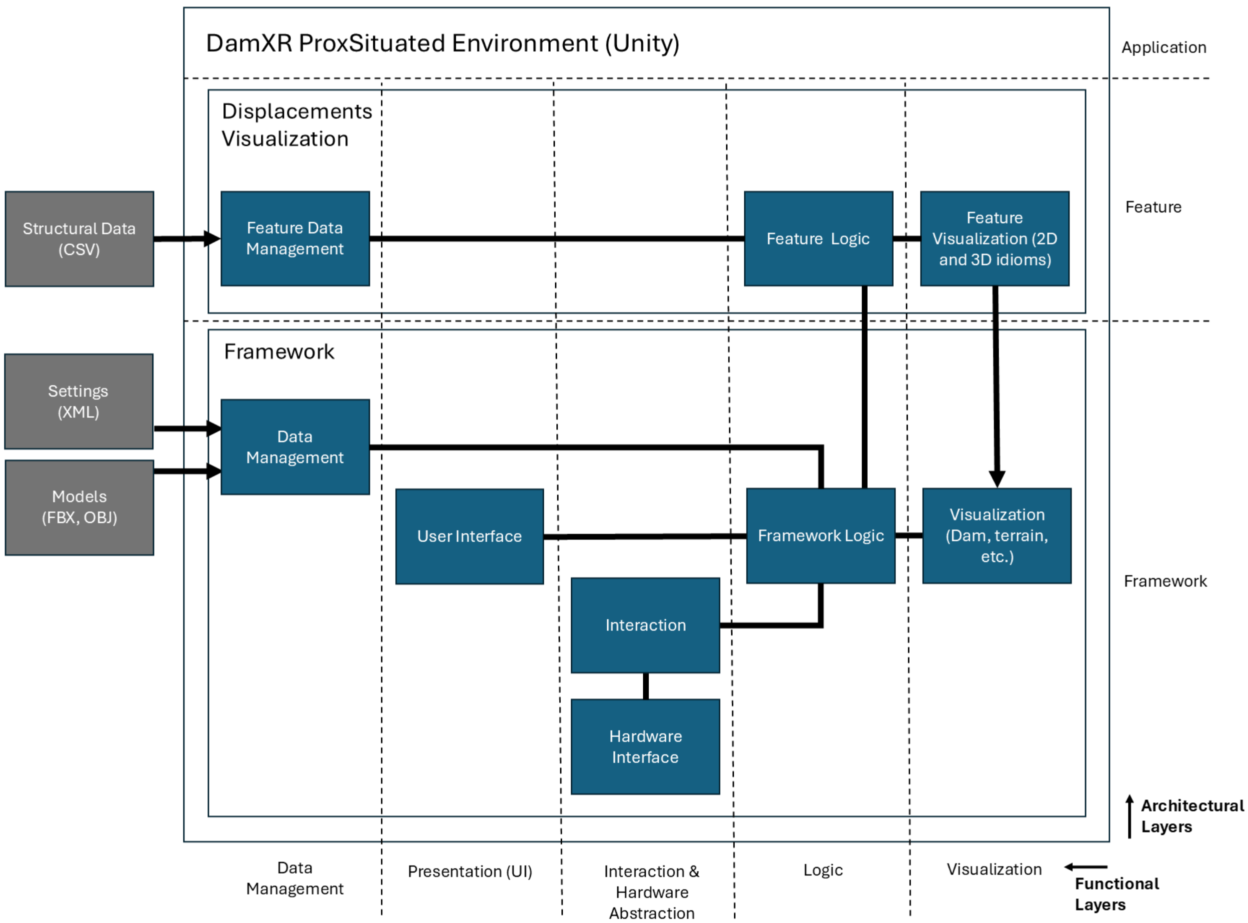


Figure 5.2: System architecture for the base framework on the bottom and the displacements visualization feature on top.

Because we had previous programming experience with *Unity* (C#), we decided to use this graphical engine for the implementation of our framework. With regards to the targeted XR hardware, we opted for the *Metas' Meta Quest* headsets family. This option was due mainly to the fact that this hardware could support the participant tasks we intended to carry out for the user study. Furthermore, the overwhelming popularity of these headsets, in comparison to other models[1] would facilitate the adoption of the framework, making it more

[1]Global XR (AR & VR Headsets) Market Forecast: https://www.counterpointresearch.com/report/

accessible to a broader developer base. Meta also offers comprehensible hardware abstraction with its *Meta XR Interaction SDK* which can take full advantage of the chosen hardware model family.

The framework was designed to abstract the following aspects:

- Reservoir water occlusion: As we will see later in this dissertation, representing water reservoirs can be challenging, especially when a specific application requires a variable water level. The framework can abstract this process;

- Sensor network representation: Sensors networks can be represented by loading the geometry of the sensors/marks and defining their relative placement using external settings files (.XML);

- User interface adaptive menus: The framework provides a UI component library. It also provides an adaptive mechanism that will render the menus in *Unity's World Space* or *Screen Space* depending on the device being used (XR or PC);

- Gesture activated wrist UI menu: The framework offers a pre-built mechanism for activating a wrist menu. To access this menu, users have to rotate their left forearm and wrist, just as if they were going to check the time on a real watch;

- Floating panels for data representation: These panels can be used to represent *e.g.,* 2D dam data charts. They can be dragged, scaled, and freely positioned in the virtual environment;

- Runtime model importing: The framework can be used to load on runtime both .OBJ and .FBX files (using *TribLib 2*) and render them in the virtual environment;

- Handling user interaction and locomotion across AR, VR and PC: The framework handles user interaction with gestures, controllers, mouse, and keyboard. It translates that interaction to consistent actions depending on predefined, configurable locomotion paradigms for each of the XR modalities;

- Transitioning between AR and VR seamlessly, in the same user session;

- Device detection: The framework allows the detection of which type of device is currently being used (XR headset or desktop PC), which enables adaptive interfaces;

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As such, the *DamXR* framework provides a modular set of base functionalities. This modular facet of the framework enables a free, non-rigid development pipeline for new dam safety control features.

The functionalities are optional and can be configured using external settings files or directly within the application. While they are targeted for *proxsituated* dam safety control applications, many of the above functionalities could, in fact, be applied to other domains.

5.2.1 Data management

At the framework level, the data management module is used for loading the 3D models that will integrate the *proxsituated* environment. These can include the dam structure, the terrain, and the bodies of water. They can also include feature-specific models, such as sensors and other components of dams.

This module also allows reading and parsing configuration files concerning aspects such as model positioning and orientation, reservoir attributes, sensor networks geometry, UI menus structure, floating panels properties, and locomotion characteristics for each mode.

At the feature level, the data management module is responsible for loading and parsing all the data needed to implement the functionality of that specific feature. For our proposed displacement visualization feature, this module loads and parses a structural time-dependent dataset from a .CSV file. This dataset contains the evolution of registered displacements over time for each sensor (geodetic mark) position. It also includes the theoretical displacements calculated using prediction models for each of those sensors/marks positions. Furthermore, it incorporates auxiliary data such as the water levels registered over time (at dates corresponding to when the displacements were registered).

5.2.2 User Interface

The framework includes a UI component library (Figure 5.3) that can be used to build cohesive user interfaces across new features, thus providing consistent user experiences. The components were designed to mimic the default system *MetaQuest* UI look and feel (which, to the best of our knowledge, is not publicly available for programmers to use), thus further contributing to the consistency of the user experience.

The interfaces can be pre-built using external .XML configuration files (loaded and parsed through the data management module) or directly on the *Unity* editor. The following components are included in the UI library: forms, labels, buttons, switches, radio buttons, picture boxes, sliders, and numeric up-down.

Depending on the device the framework detects as being currently used (XR headset or desktop computer), the UI menu components will be rendered in *Unity's World Space* or *Screen Space*. Such a mechanism provides an adaptive UI that preserves menu systems' look and feel across devices.

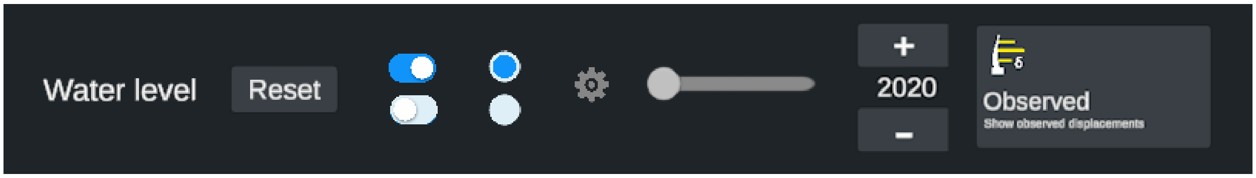


Figure 5.3: Set of UI library components.

5.2.3 Interaction

The interaction module bridges the hardware interface and the logic module. The XR hardware interface is abstracted via the *Meta XR Interaction SDK*. The user input is then interpreted by the interaction module, which maps it to specific actions in the virtual space. The characteristics of these actions depend on what was predefined for each of the modes (VR, AR and PC), namely the locomotion paradigm. This predefinition is carried out using a settings file loaded and parsed using the data management module and relayed to the interaction module via the logic module (where the settings files are interpreted).

An example of such mapping of input to specific actions concerns how user input results in locomotion in the virtual environment. Suppose the settings of the application define the locomotion in VR as egocentric [34]. In that case, when users press, *e.g.,* the forward button in the controller joystick, they stay static, and the world model moves closer, giving them the illusion of moving forward. However, supposing the locomotion in AR was defined as exocentric [51]. When users press forward, they stay static, and the world model moves forward, making them aware that they are manipulating the relative position of the model. *DamXR*'s framework approach to locomotion in the virtual world will be detailed later in the document.

The framework also offers a pre-built XR interaction mechanism for activating a wrist UI main menu. To access this menu, users have to rotate their left forearm and wrist, just as if they were going to check the time on a real watch. The interaction with menu items is carried out using a selection ray coming out of the right controller that users can point to a specific UI element and press the controller index trigger to select it.

5.2.4 Logic

The framework logic module sits at the functional center of the framework. It plays a core role in handling the data flow from and to the other modules and carrying out the calculations needed for the system to work. First, it is in charge of interpreting the settings values parsed at the data management module and applying them. As we have seen, these settings concern a multitude of aspects of the system, including the positioning of 3D objects inside the virtual environment or the characteristics of the locomotion within the virtual environment.

The framework logic module is also responsible for triggering the actions pertaining to UI events. In that concern, it establishes the connection between user interaction and the UI interface. To that end, it performs the needed computations, outputting the results to the visualization module so that the requested actions in the virtual environment (*e.g.,* the rotation of the dam structure) can be represented.

At the feature level, the logic module establishes the connection with the framework (via the framework logic module) but also serves as an intermediary between the feature management module and the feature visualization module. In that scope, it handles the computations needed to implement the functionality offered by a specific feature.

For our displacements visualization feature, the feature logic module is responsible for handling the structural data parsed in the feature data management module and computing the derived measures needed to represent the idioms. The computed measures are then used in the feature visualization module to render the 2D idioms in the floating panels and the 3D idioms directly over the dam model.

5.2.5 Visualization

The visualization module is responsible for rendering the virtual environment. This environment includes the dam model, the terrain, and the water bodies, but also all models resulting from the features that run on top of the framework, like the sensor network (as is the case with the displacements visualization feature).

The visualization module is also an integral part of specific abstraction functionalities offered by the framework. Such functionalities include the dynamic water reservoir representation and the sensor network rendering. These specific functionalities will be discussed in detail in the following sections.

At the feature level, the visualization module is responsible for rendering the 2D and 3D elements resulting from the specific outputs the feature implements. In the case of the displacements visualization, the feature visualization module ensures the representation of the 2D idioms on panels and the 3D idioms directly over the dam.

5.3 Locomotion Abstraction

A relevant abstraction offered by the framework is the built-in virtual environment locomotion. The developer can set the characteristics of the locomotion for each of the modes (AR, VR, and PC) by configuring the corresponding settings. The framework will handle the distinct input devices the developer wishes to use for each mode (*e.g.,* XR controllers, hands, mouse, and keyboard) and signals (*e.g.,* button press, hand pose) and translate them to actions in the virtual world according to the chosen locomotion paradigms for each mode.

The following properties can be configured in the scope of virtual environment locomotion:

1. Mode(s) the application will support: AR, VR, PC
2. Input device (for XR):
   - Controllers
   - Hands
3. Locomotion paradigm for each mode:
   - Egocentric (ego-motion)
   - Exocentric (world-motion)
4. Gaze-mode-navigation use for each mode:
   - Use headset/head gaze (XR) / mouse pointer as gaze (PC) navigation
   - Use controller-joystick-based (XR) / keyboard-based translation/rotation (PC)
5. Snap-turning [76], [80] use (for VR):
   - Snap-turning
   - Smooth-turning
6. Point to teleport (for VR):
   - Use teleportation
   - Don't use teleportation

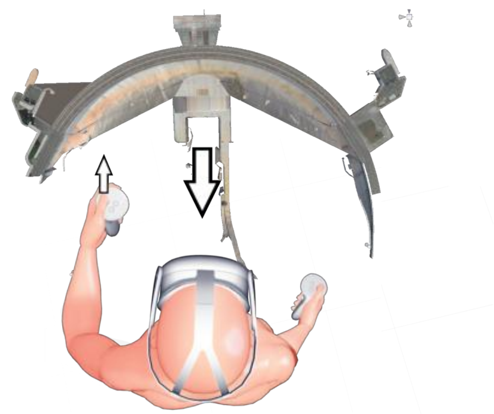
The framework is primarily aimed at combined room-scale (physical) and smooth (continuous) locomotion (with optional snap-turning for VR). For applications where vast distances need to be traveled in the virtual environment, teleportation-based navigation can be used in combination with the former. This functionality can be activated in the settings, enabling the user to point a selection ray at a certain point in the terrain and be teleported there. An example of how such functionality can be helpful for specific applications will be addressed in Section 5.11.

For the framework locomotion abstraction we adopted a concept that enables a smooth transition between ego and exocentric locomotion. This transition is especially relevant when both AR and VR modes are used interchangeably in the same application, as the former is commonly associated with exocentric locomotion and the latter with egocentric.

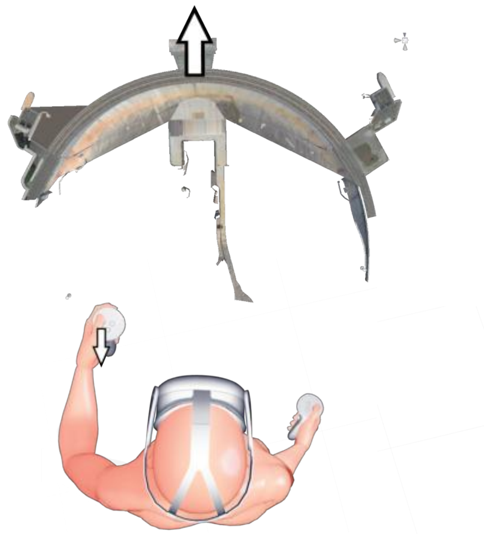
In our frameworks' virtual environment, if the user does not move physically, the player/camera remains fundamentally stationary. In order to create the illusion of movement, *e.g.,* forward translation, when the user presses the controller's joystick forward, it's instead the set of all virtual objects inside the environment that, as a whole, moves. If we are in the VR egocentric mode, when the user presses the joystick forward, the model of the dam moves backward, creating the illusion that the user is locomoting forward in the virtual environment. However, if we are in the AR exocentric mode, when the user presses the joystick forward, the model of the dam moves forward as if the user was manipulating it.

In Figures 5.4 and 5.4, we exemplify how, based on this general concept, the framework translates user input to specific locomotion actions in the virtual environment, depending on the chosen paradigm.

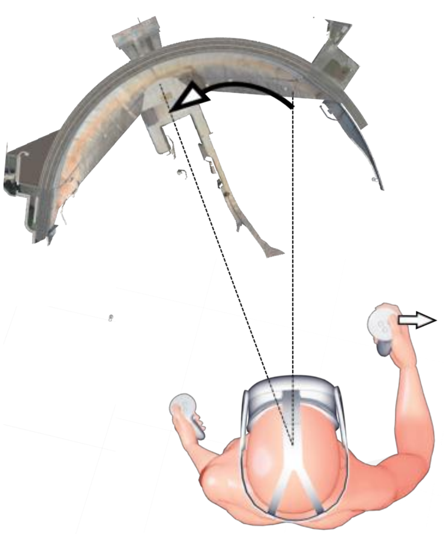
For our *DamXR* proxituated structural displacements visualization, we used the three modes (AR, VR and PC), and we opted for selecting controllers as input devices. Regarding locomotion paradigms, we configured the framework for using the egocentric paradigm in the VR mode and the exocentric in both AR and PC.



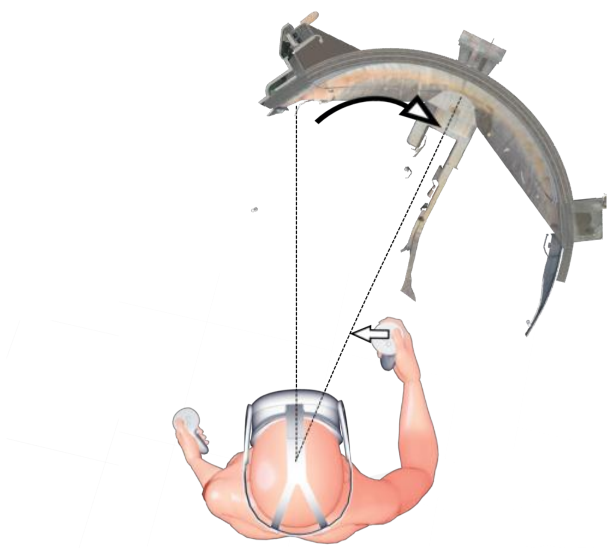
(a) The model moves backward to give the illusion to users that they are moving forward



(b) The model moves forward to give the illusion to users that they are moving backward

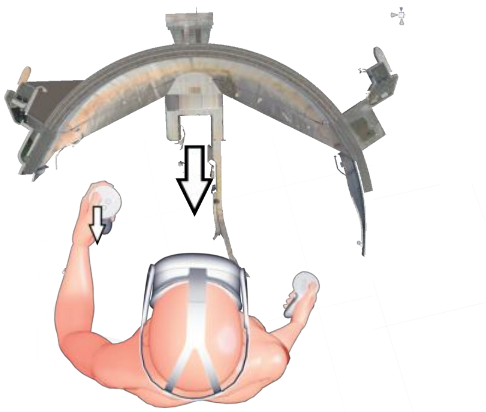


(c) The model rotates anticlockwise around users to give them the illusion that they are rotating clockwise around themselves

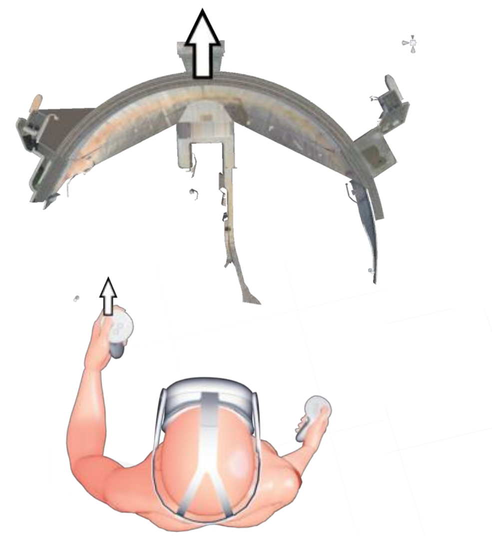


(d) The model rotates clockwise around users to give them the illusion that they are rotating anticlockwise around themselves

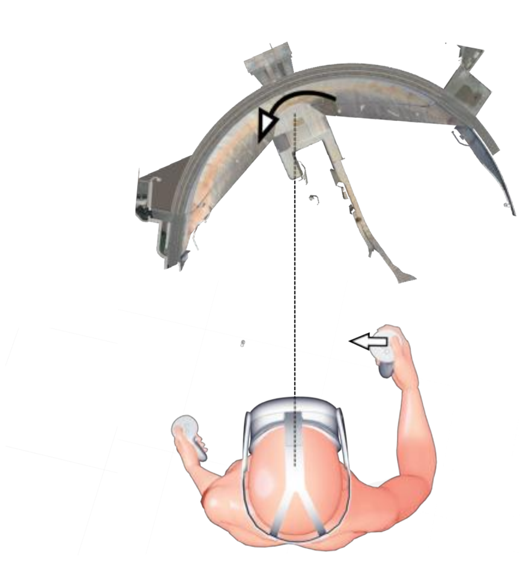
Figure 5.4: An example of how the framework handles controller-based egocentric locomotion by creating the illusion of motion by translating/rotating the model in the opposite direction to the controller joystick.



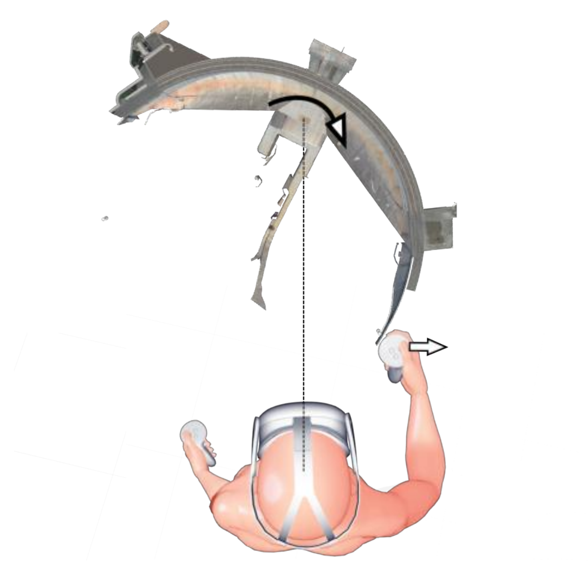
(a) The model moves backward when users push the controller joystick down



(b) The model moves forward when users pull the controller joystick up



(c) The model rotates anticlockwise around itself when users move the controller joystick left



(d) The model rotates clockwise around itself when users move the controller joystick right

Figure 5.5: An example of how the framework handles controller-based exocentric locomotion by giving them the awareness that they are manipulating the relative position of the model.

5.4 UI Interaction and Functionality

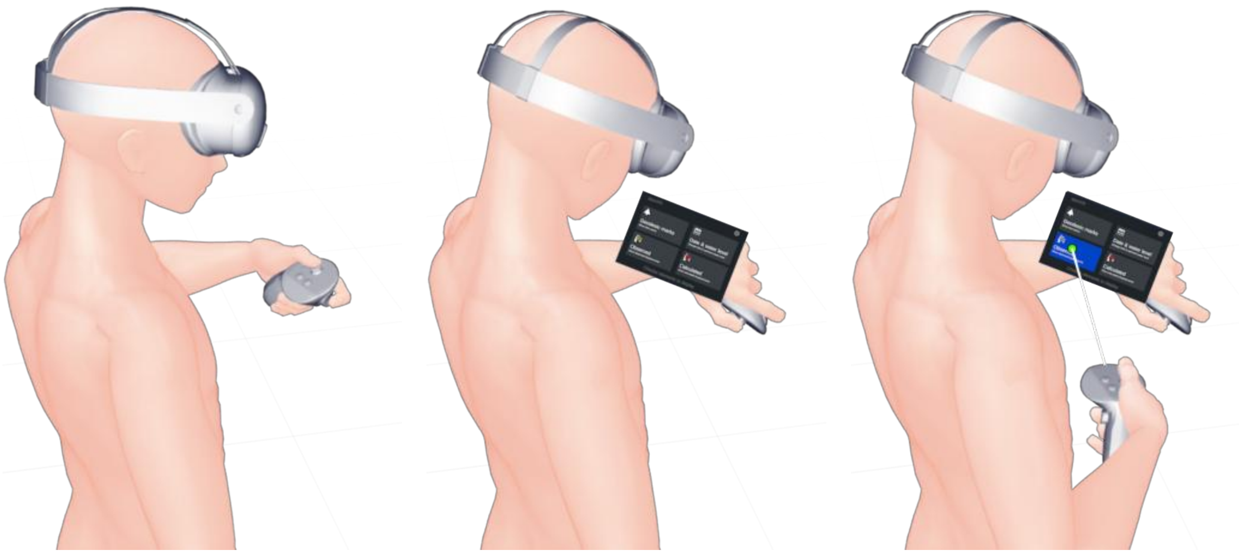
The UI is a determining component of the operation of any XR system. This section will cover the general functioning of the *DamXR* structural displacements visualization applications' UI and address its integration with aspects such as data representation and reservoir water levels representation.

Users are initially placed in front of a dam structure. They can move around the structure and visualize its downstream and upstream faces. They can also see the downstream water body representation and the upstream water reservoir. In the VR mode, they can equally visualize the surrounding terrain and sky.

The application uses the frameworks' built-in gesture-activated wrist menu as the main UI (Figure 5.6). To access this menu, users have to rotate their left forearm and wrist, just as if they were going to check the time on an actual watch (Figure 5.7 (a) (b)). The interaction with menu items is carried out using the controllers' selection ray and the index trigger button for selections (Figure 5.7 (c)).

Figure 5.6: The built-in gesture-activated wrist menu provided by the *DamXR* framework used in the displacements visualization application.

The main menu comprises four large buttons representing the distinct data visualization layers, the geodetic mark network, and the observation date and water level selection. Selecting the geodetic marks button triggers the representation of the geodetic marks network over the dam structure. This representation can be used to find specific marks by their



(a) (b) (c)

Figure 5.7: To access the gesture-activated wrist menu, users have to rotate their left forearm and wrist, just as if they were going to check the time on a real watch (a) (b). The interaction with menu items is carried out using the controllers' selection ray and the index trigger button for selections (c).

reference code or relative position along the dams' structure downstream face.

The bottom buttons 'Observed' and 'Calculated' toggle the visibility of the structural displacements idioms. These idioms are conceptually bar charts, representing the magnitude of displacements. They have a distinct arrangement depending on where they are represented. Their representation in floating panels is done in 2D. Their representation directly overlaid to the dam structure, is done in 3D.

As mentioned previously in this chapter, the observed displacements are measured in geodetic marks located downstream of the dam. The calculated displacements are obtained via theoretical prediction structural models for those same mark positions.

The fourth button, located in the top right corner of the main menu, gives users access to two flyout panels, which slide out from the right side of the main menu panel (Figure 5.8). The top flyout panel lets users enter a specific observation date to view the structure's displacements. This date corresponds to when the observed displacements were registered/observed.

In the bottom flyout panel, users can visualize the reservoir water level registered for the above-mentioned selected date. Users can also select a specific water level to visualize a typical theoretical displacement distribution along the dam structure for that water level.

While selecting the observation date or the water level, the users can observe a representation of the reservoir's water level changing. A simplified representation of the water bodies is displayed for AR and PC. For VR a more realistic representation of the upstream reservoir and other water bodies is displayed.

On the top right corner of the main menu, there is also a cogwheel button that enables users to access the options sub-menu. In this menu, they can alternate between the different XR modes (AR and VR) seamlessly. They can also toggle the panel's mode, which shows/hides the floating data panels while hiding/showing the data represented over the dam, thus alternating between data representation spatial indirection levels.

The options menu also allows users to alternate between the visual detail levels. They can toggle the representation of objects with photographic textures or without any textures (flat shading). Furthermore, this menu also enables the selection of the UI language (Portuguese or English) and reset the model to its default position.

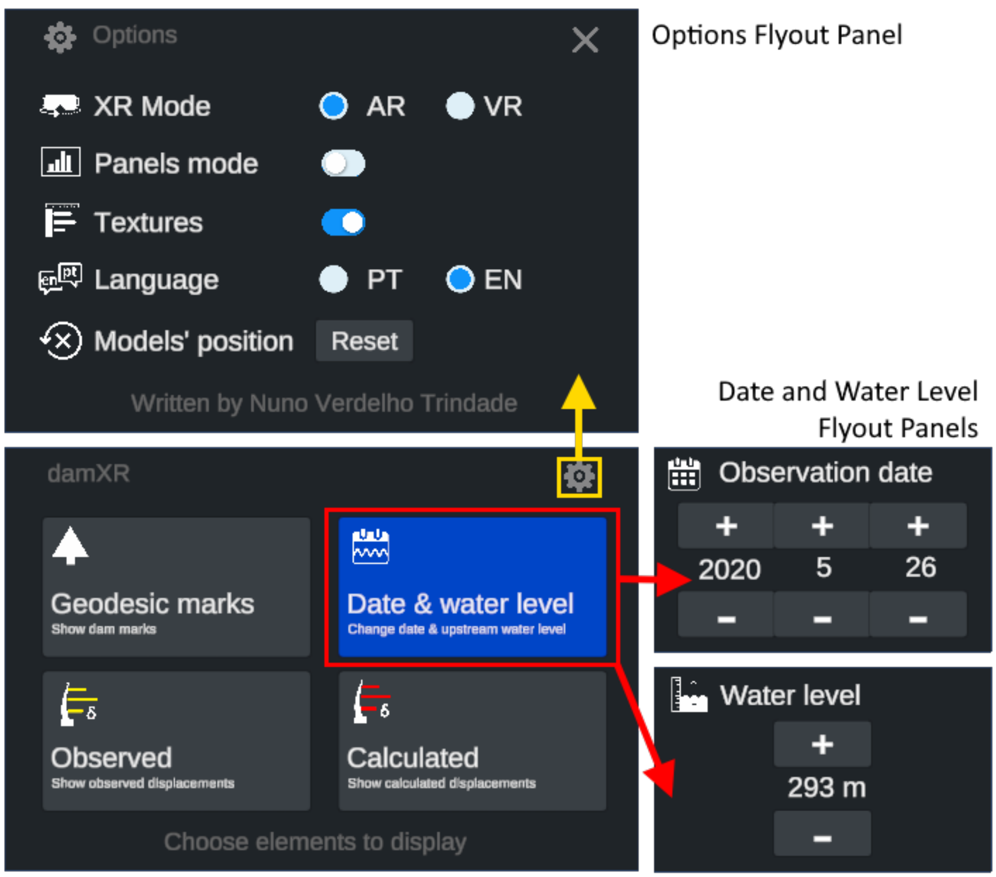


Figure 5.8: Accessing the 'observation date' and 'water level' flyout panels (red arrows) and the options flyout sub-menu (yellow arrow) from the main menu.

5.5 Visual Detail

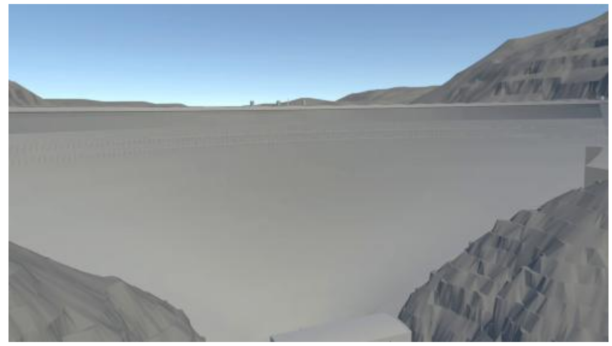
The possibility of varying the visual detail was one of the core aspects of our *DamXR* displacements visualization application. This importance came from the fact that one of our thesis objectives was to evaluate the influence of visual detail in data analysis performance and user experience in *proxsituated* environments.

To support the thesis objectives, we focused on varying a specific aspect of visual detail - the textures - while keeping other aspects constant, such as geometrical mesh complexity and lighting. As a simplification, we also chose to test only the two boundary conditions: photographic textures and flat shading (no textures).

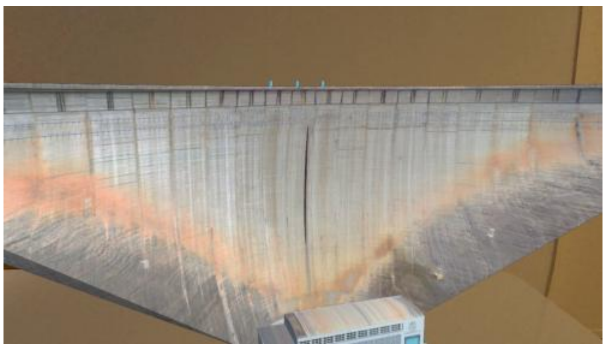
As such, our displacements visualization application allows users to configure the level of detail they want the virtual environment to have. This configuration can be carried out using the options menu, as Section 5.4 mentions.

For the user study, the detail level was automatically configured to present the participants with the relevant visual detail for each test round. Figure 5.9 depicts the two boundary visual detail conditions for each mode tested.

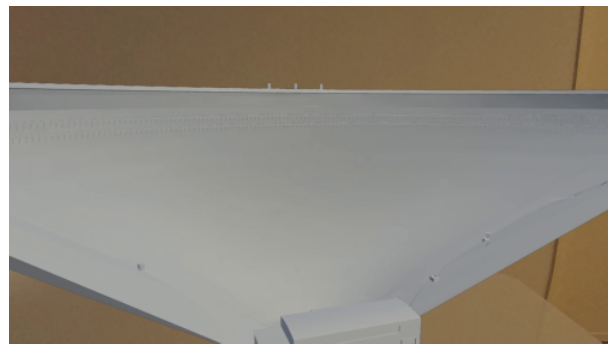
(a) VR mode with a higher level of visual detail (textures)



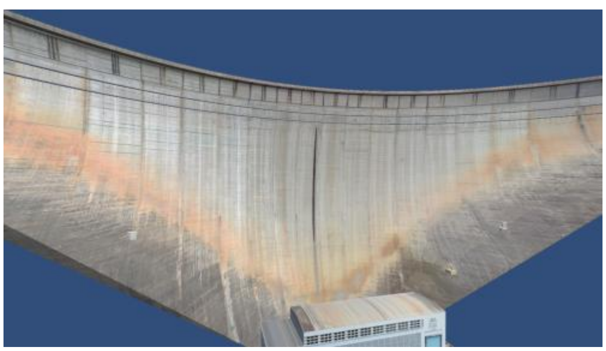
(b) VR mode with a lower level of visual detail (no textures)



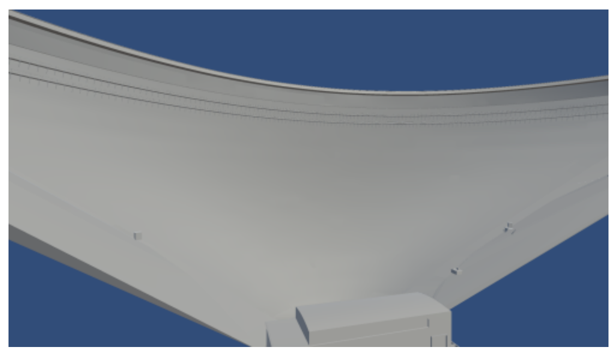
(c) AR mode with a higher level of visual detail (textures)



(d) AR mode with a lower level of visual detail (no textures)



(e) PC mode with higher level of visual detail (textures)



(f) PC mode with a lower level of visual detail (no textures)

Figure 5.9: The two different levels of visual detail for each mode.

5.6 Data Representation Spatial Indirection

Another important requirement of our *DamXR* displacements visualization application was the possibility of varying how the data was presented to the user. Indeed, one of our thesis objectives was to evaluate the influence of spatial indirection of the data representation in data analysis performance and user experience in *proxsituated* environments.

In particular, we needed a way to represent displacement datasets at distinct spatial indirection levels. We chose two different conditions corresponding to distinct levels of indirection: the representation of data in 2D traditional charts[2], displayed in floating panels (higher spatial indirection) and the representation of 3D idioms directly superimposed over the dam structure (lower spatial indirection).

We chose a 2D idiom for the higher indirection variant to have a condition closer to the more conventional way of representing displacement data. We chose the 3D idiom for the lower indirection variant because we wanted to consider in our analysis the possible benefits, on depth and spatial perception, brought by this spatial data representation, in XR-powered analysis.

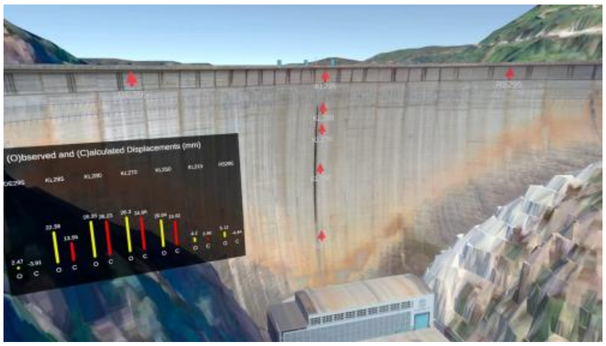
The characteristics chosen for the two spatial indirection variants may raise, however, some questions in terms of their comparability. Indeed, one is a 2D vertical bar chart, and the other one is a 3D horizontal bar chart that follows the geometry of the dam's downstream face.

In this regard, in a study on the impact of bar chart orientation, Fischer *et al.* [52] observed longer decision times in comprehension tasks for horizontal bar charts when compared to vertical. Furthermore, Hughes [68], in a bar chart accuracy assessment study, observed how participants could perceive smaller differences in the 2D bar charts in comparison to 3D ones.

However, as we will see further on, in our user study on Chapter 6, our findings contrasted with those of the referenced studies above, showing an opposite trend. Indeed, the variant that used horizontal 3D bar charts corresponded to lower completion times and higher task success than the variant with vertical 2D bar charts.

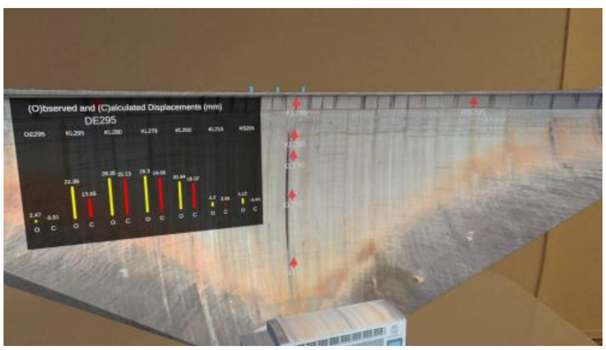
In Figure 5.10, we can see how the two different levels of (structural displacements) data representation spatial indirection was materialized in the virtual environment for each of the addressed modes, with a higher visual detail referent. Moreover, in Figure 5.11, we can see the same, but for the lower visual detail variant.

[2]The *Graph And Chart Unity* asset was used for rendering the 2D bar charts inside the panels.

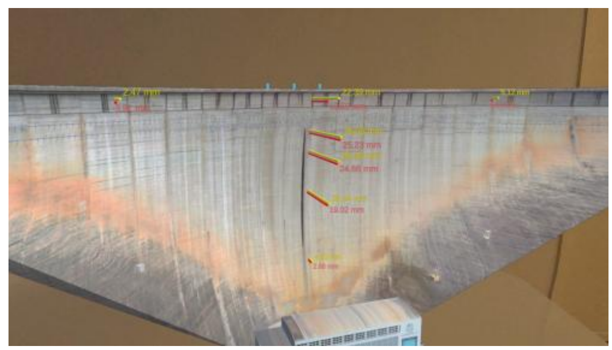


(a) VR mode with a higher level of spatial indirection (charts in panels)

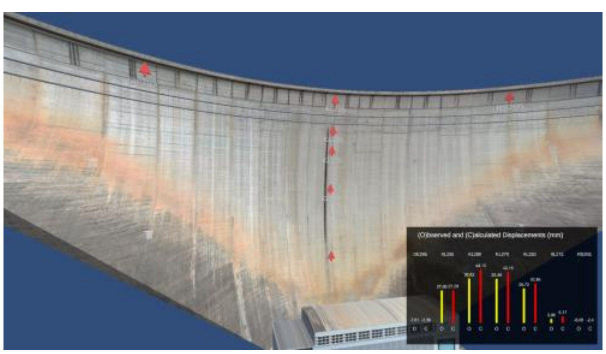
(b) VR mode with a lower level of spatial indirection (overlaid to the structure)



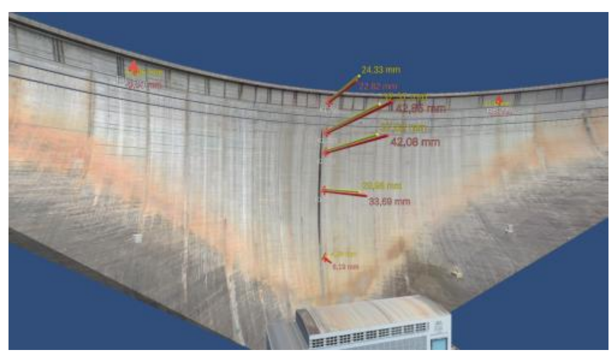
(c) AR mode with a higher level of spatial indirection (charts in panels)



(d) AR mode with a lower level of spatial indirection (overlaid to the structure)

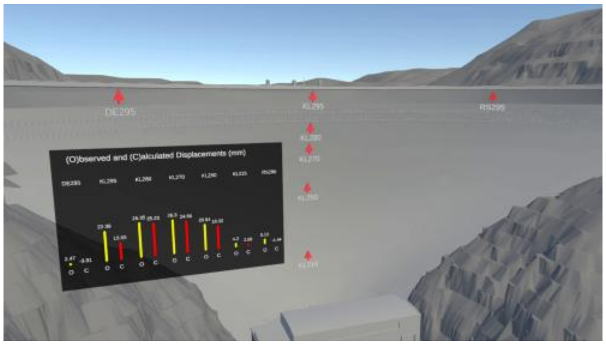


(e) PC mode with a higher level of spatial indirection (charts in panels)

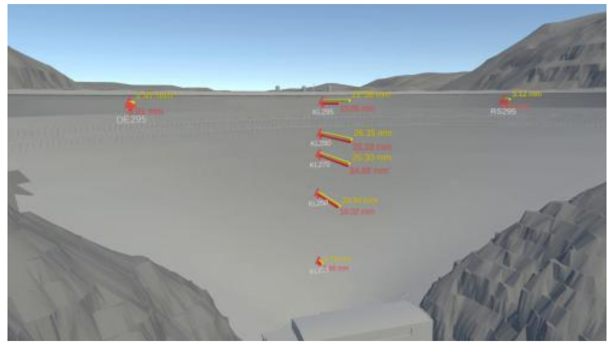


(f) PC mode with a lower level of spatial indirection (overlaid to the structure)

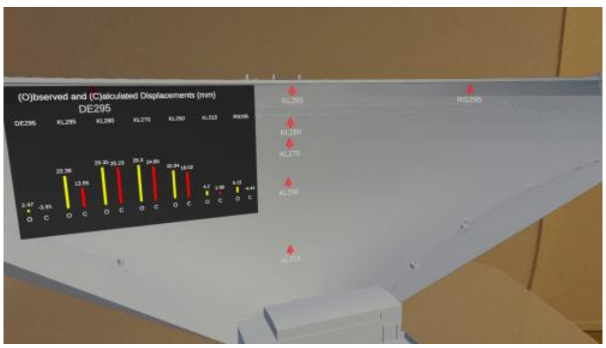
Figure 5.10: The two levels of (structural displacements) data representation spatial indirection for each mode, with a higher visual detail referent. The sensor network geometry is always represented over the structure.



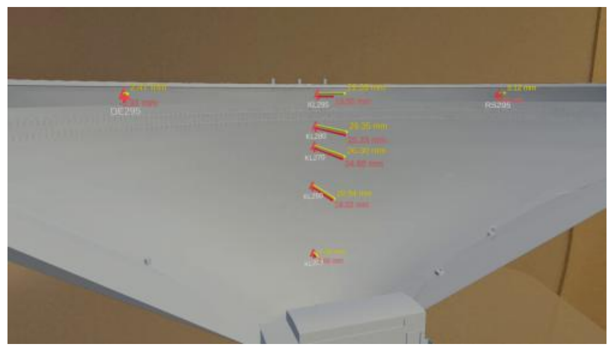
(a) VR mode with a higher level of spatial indirection (charts in panels)



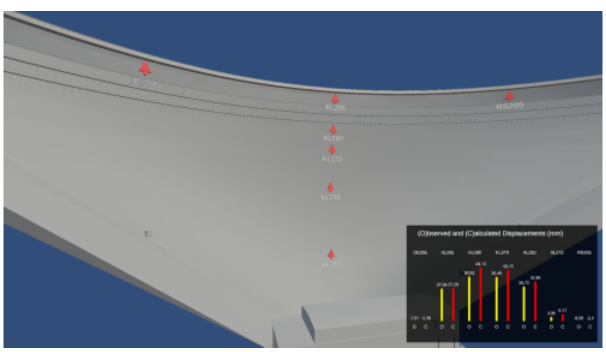
(b) VR mode with a lower level of spatial indirection (overlaid to the structure)



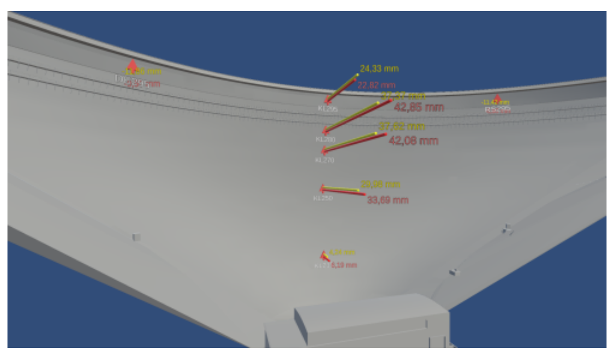
(c) AR mode with a higher level of spatial indirection (charts in panels)



(d) AR mode with a lower level of spatial indirection (overlaid to the structure)



(e) PC mode with a higher level of spatial indirection (charts in panels)



(f) PC mode with a lower level of spatial indirection (overlaid to the structure)

Figure 5.11: The two different levels of (structural displacements) data representation spatial indirection for each mode, with a lower visual detail referent. The sensor network geometry is always represented over the structure.

5.7 Manipulating Floating Panels

Floating panels for data representation are an integral part of the *DamXR* framework. They are used in the displacement visualization feature/application to display the calculated and observed displacements' time-dependent datasets.

The framework abstracts the display but also the interaction/manipulation of these floating panels in the virtual environment for the distinct devices and modes. With that objective, users can use the XR controllers to point a selection ray at a panel, press the index trigger button to 'grab' it, and drag it to the most convenient location for their task. When in the PC mode, the panels (rendered in *Screen Space*) position can be manipulated using a drag-and-drop mouse action.

A second, less conventional, XR manipulation technique for positioning floating panels was also implemented in the scope of the interaction abstraction offered by the framework. This second technique does not require pointing a ray at the panel. In fact, this action is not always the most precise, especially when the panel is located at a certain distance from the user.

Instead, the second technique uses head-directed object placement to grab and place the panels at a specific point in the virtual environment. Users can initiate the action by pressing the controller hand trigger, which signals the system to 'grab' the panel and reposition it in front of them. In this initial step, the panel remains at a certain distance from the head and is oriented in the head-gaze direction. With the object now anchored in front of the user's head, they can manipulate its position within the virtual environment by moving their head. They can also change the relative distance from the panel to the user's head using the left controller's joystick to increase or decrease this distance. When the users are satisfied with the object's placement, they release the hand trigger, 'unanchoring' the panel and placing it in its final position (Figures 5.12 and 5.13).

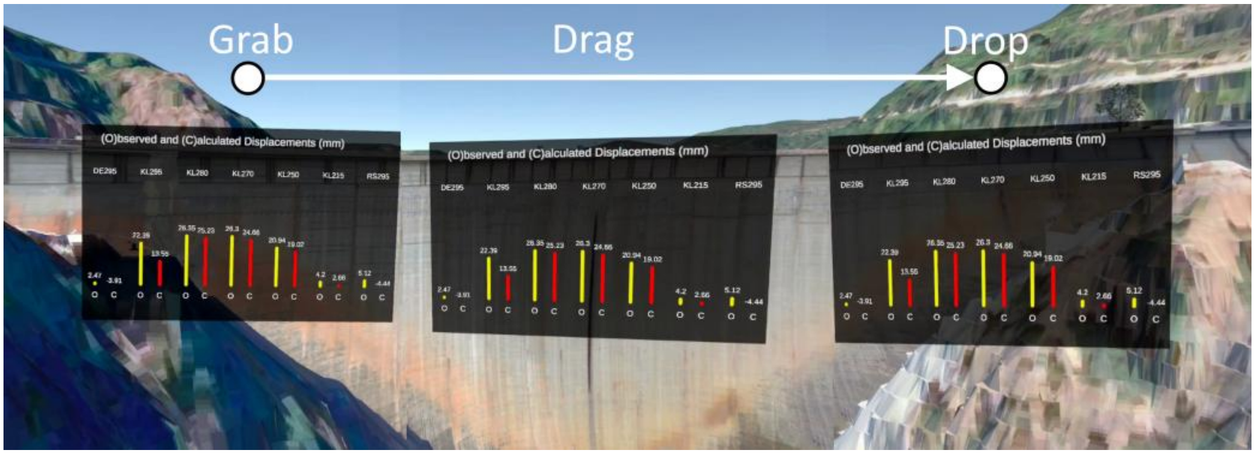
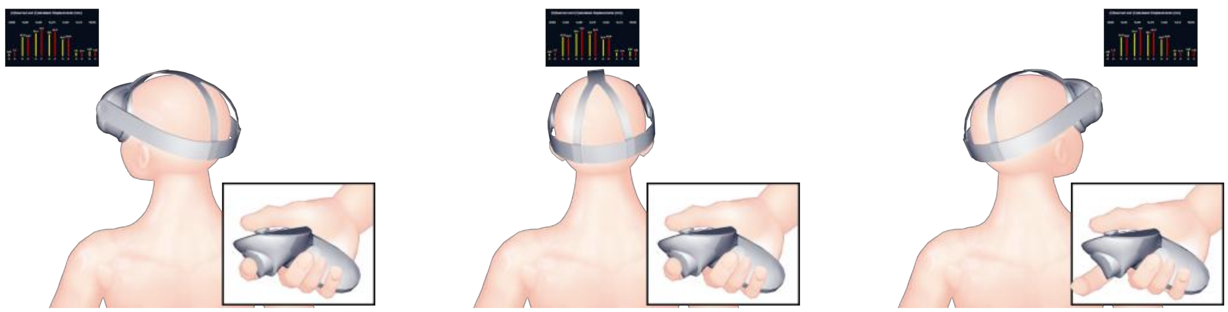


Figure 5.12: Using the head-directed object placement technique to move the panel across the virtual environment to the opposite side of the dam (screenshot montage).



(a) (b) (c)

Figure 5.13: With head-directed object placement, users start by pressing the controller trigger to move the panel to a position at the front of their headset (a). Without releasing the trigger and with the panel now anchored, they can drag it within the virtual environment by moving the head (b). When the users are satisfied with the object's placement, they release the hand trigger, 'unanchoring' the panel and placing it in its final position (c).

5.8 Sensor Network Representation

The representation of sensors and other devices in the interior of models of dam structures (*e.g.,* accelerometers or plumb lines) or marks in the downstream face can be a very relevant functionality in a dam safety control application. Indeed, most examples addressed in Chapter 4 involved some type of sensor or mark network representation. Given this relevance, it was only logical for the framework abstraction layers to include this representation.

At the framework level, the sensor network representation pipeline is carried out at runtime and begins at the data management module. Here, a settings file containing positional and orientation data and information concerning the types of sensors that integrate the network is loaded and parsed.

Positional data can be provided in two distinct formats: absolute world coordinates or local/relative coordinates to a reference point (provided by the user) in the dam model. The first format is useful when we know the exact elevation of each individual sensor. The second format is useful when we want to represent the sensor network in relation to a notable reference point in the dam structure.

An example would be representing a group of accelerometers located every 20 meters along a maintenance gallery in the dam's interior. For the first format, we would use the individual world coordinates of each accelerometer. For the second format, we would use the world coordinates of a notable reference point inside the gallery (*e.g.,* the start of the gallery or the first accelerometer) and local/relative coordinates for each of the accelerometers.

It is also in the data management module that the geometry of each of the distinct types of network sensors is loaded as 3D model files. At the logic module, each individual sensor unit (with its own set of positional and orientation data) is then associated with a specific sensor 3D model. It is also at this stage that the distinct types of sensors are linked in logic groups for later, making it easier to show/hide a particular type of sensor. Finally, at the visualization module, the full sensor network model, with the correct positioning and orientation, is rendered in the virtual environment.

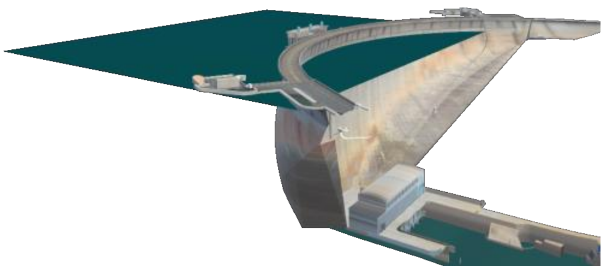
5.9 Reservoir Water Occlusion

Due to the physical settings of dams, the representation of bodies of water in XR dam safety applications is frequently relevant. The water behavior in these bodies of water can be accurately simulated using methods such as real-time particle-based fluid simulation, which can offer high levels of detail and realism. However, such an approach is generally too computationally expensive and, therefore, not ideal for the limited processing power of current XR headsets.

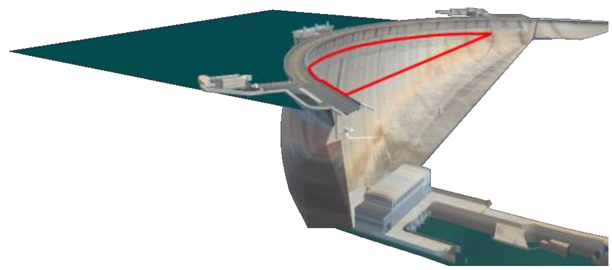
An alternative, less computationally expensive method for representing water bodies is shader-based fluid effects. This method utilizes shaders to create the illusion of fluid behavior. As such, it focuses primarily on visual representation rather than physical accuracy. This method can visually simulate ripples, waves, and surface reflections in the water, giving users the illusion of fluid dynamics.

For decreased computational overhead, the shader-based fluid effects are typically applied to a horizontal four-sided polygon (a 'quad') to simulate the water plane. In the geometrical settings of the dam's surrounding terrain, the use of such planes is generally straightforward. Such straightforwardness comes from the fact that when the water plane interpenetrates the terrain mesh, the physical overlap of the former is clipped (occluded) by the latter. So, an illusion is created that the water plane is delimited by the terrain. For this reason, even with variable water level representation, the rise and fall of the water level is not problematic.

A problem with this approach may arise in the context of the intersection of the water plane with certain types of dam structures. For structures like gravity dams with straight upstream faces, the water plane interpenetration with the structure does not pose a problem as the clipping of the water plane is carried out by the structure itself, similarly to what happens with the terrain. However, for arch dams (as is the case of our case study, the *Cabril Dam*), the water plane interpenetration will likely spill beyond the downstream face, breaking the illusion of the water being delimited by the dam, as exemplified in Figure 5.14 (a). This problem is even more glaring when we intend to make the water level vary instead of using a static water plane representation.



(a) Without object occlusion, the water object spills beyond the downstream dam face



(b) An occlusion mesh (in red) with the dam upstream arch profile is used for preventing the spilling

Figure 5.14: The framework enables reservoir water bodies representation, with built-in object dynamic occlusion (b) to prevent the water plane representation from spilling beyond the upstream dam faces (a).

The *DamXR* framework tackles this problem by using an occlusion mesh with the geometry of the dam upstream arch profile as illustrated in Figure 5.14 (b). For that, the developers must load both the dam arch profile mesh model and the dam structure model into the framework. The framework will then automatically apply an occlusion shader to that mesh. This shader is used to control the visibility of certain objects (the water plane in our case) in relation to the mesh.

Because the occlusion mesh will follow the vertical movement of the water plane as the water level varies (Figure 5.15), developers will also have to configure the characteristics of this movement. With that objective, first, the water plane settings have to be configured in order to provide the framework with its size and location (given that the water plane is generated at runtime) as well as the upper and lower positional limits of the vertical movement (in the case of a non-static water level).

The settings for the occlusion mesh also have to be configured. These settings include the initial position and orientation. Moreover, because in arch dams, the arch typically reduces in diameter as we go from the top to the bottom of the dam, we would not be able to use the same occlusion mesh effectively at a level other than the initial position. To deal with this characteristic, the water plane settings include a configurable set of increments (step sizes). These increments allow the framework to deform the occlusion mesh longitudinally or transversely as the water level falls or rises. There are also configurable increments to regulate the occlusion mesh's longitudinal and transverse position variation.

This increment mechanism will naturally not adapt the occlusion mesh perfectly to the dam profile in positions other than the initial due to the complex geometry or arch dam faces. However, because some water plane spilling is allowed inside the dam structure as long as it does not spill beyond the downstream face, the mechanism is good enough to create an adequate illusion, as illustrated in Figure 5.15.

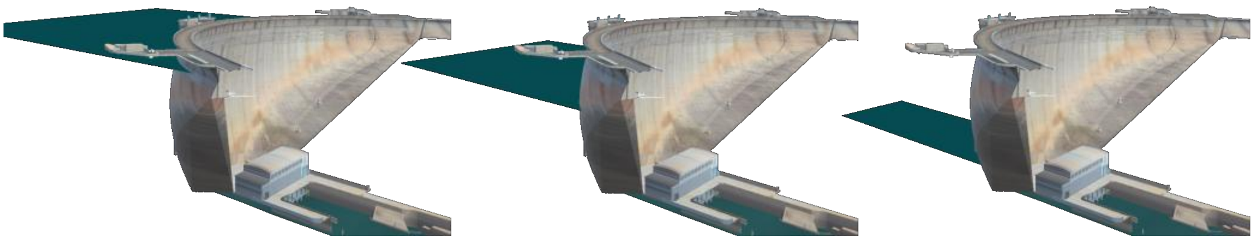


Figure 5.15: The occlusion mesh will follow the vertical movement of the water plane as the water level varies. This aspect is particularly important in applications requiring variable water level representation, such as our displacement visualization application.

5.10 Large Terrain Rendering

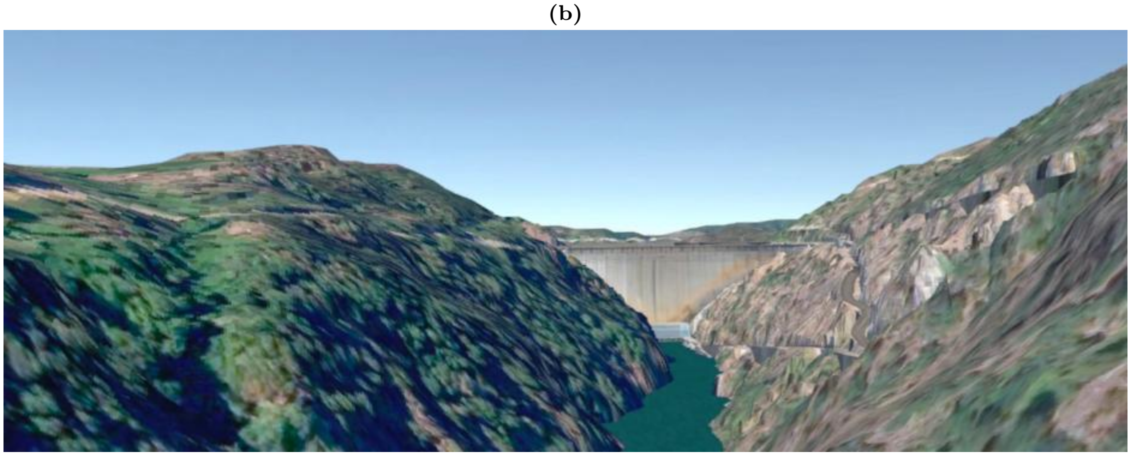
One last characteristic of the framework worth mentioning is the ability to use large terrains in the virtual environment. The framework handles large terrains with a variable LOD mechanism to complement the graphical engines' existent culling processes. This mechanism is integrated with *Unity's LOD Group* component and works by adjusting the terrain model version dynamically, based on the user's distance from the ground level.

For that purpose, multiple versions of the terrain, with distinct detail levels, have to be loaded into the framework using the data management module. Developers also have to configure the distances from the ground level that will determine the display of a certain version of the terrain.

As the user rises in altitude, the framework hides higher-detailed versions of the terrain and displays lower-detailed versions to improve performance. This mechanism was applied in the displacements visualization application, which includes a terrain model comprising of an area of over 300 square kilometers surrounding the *Cabril Dam*, as depicted in Figure 5.16.

(a)

(b)



(c)

Figure 5.16: To reduce processing overhead, the framework offers a variable LOD mechanism. This mechanism dynamically adjusts the terrain model version based on the user's distance from the ground level. Figures (a)-(c) show three increasing levels of model detail used in the displacements visualization application (VR mode).

5.11 Other Framework Applications

As addressed in the previous sections, the *DamXR* framework was initially used in a structural displacements visualization application. This application was implemented due to the need for a prototype that would support our user study. Later, the framework was used to support the development of two other distinct XR *proxsituated* applications: an application for the exploration of dam galleries (*GalleriesVR*) and an application for flood data visualization (*FloodVR*). Their purpose and functionality, as well as the role of the *DamXR* framework in their implementation and operation, are described in this section.

5.11.1 An application to the exploration of dam galleries

In the previous work, we focused mainly on data analysis conducted from the exterior of the dam structure. And while, *e.g.,* with *DamAR* and *DamVR* , we had an X-ray vision of the sensors in the interior of the dam, those prototypes were mainly designed for the observer to remain outside the dam.

However, a very relevant activity in dam safety control is inspecting dams from their interiors. For that, inspectors use maintenance(inspection) galleries situated in the interior of dam cores that traverse the structures. From there, they can verify the integrity of the installed instrumentation, including the structural sensor networks (among other tasks like detecting signs of pathology at the dam concrete core).

In this context, we set to develop *GalleriesVR* a *proxsituated* application for exploring and analyzing structural data from the interior of dam galleries. We wanted to understand the challenges and possibilities of analyzing structural information contextualized by the proximity of the sensors that registered the data. We focused on a particular type of sensor, the accelerometer, used to register accelerations in the structure arising from dynamic phenomena such as seismic activity.

The *GalleriesVR* application should allow users to move through the galleries, select a specific accelerometer, and visualize the accelerogram for that sensor corresponding to a seismic/dynamic event that occurred at a specific date. We again decided to use the *Cabril Dam* as a case study for this application and structural time-dependent datasets of accelerograms obtained from accelerations registered in this structure.

We first wanted to define the main settings of the application within the *DamXR* framework. We decided to restrict the operation of the application to two modes: VR and PC. We left the AR mode out because using AR passthrough in the context of this specific application would not bring relevant benefits and would not be practical. Indeed, the objective was for users to walk and be immersed inside the galleries, which left no room for the effective use of passthrough.

In terms of locomotion, we chose the egocentric option for both modes because we wanted to give the user the illusion that they were moving inside the galleries.

The architecture for the final solution of *GalleriesVR* and its integration with the *DamXR* framework is illustrated in Figure 5.17. At the framework level, the models of the dam structure and the galleries network, as well as the sensors (accelerometers) models, are loaded into the data management module. At this level, we also configured the general settings of the experience, like the modes used, the locomotion characteristics, the UI structure, the floating panels, and the initial positions of the user and models inside the virtual environment.

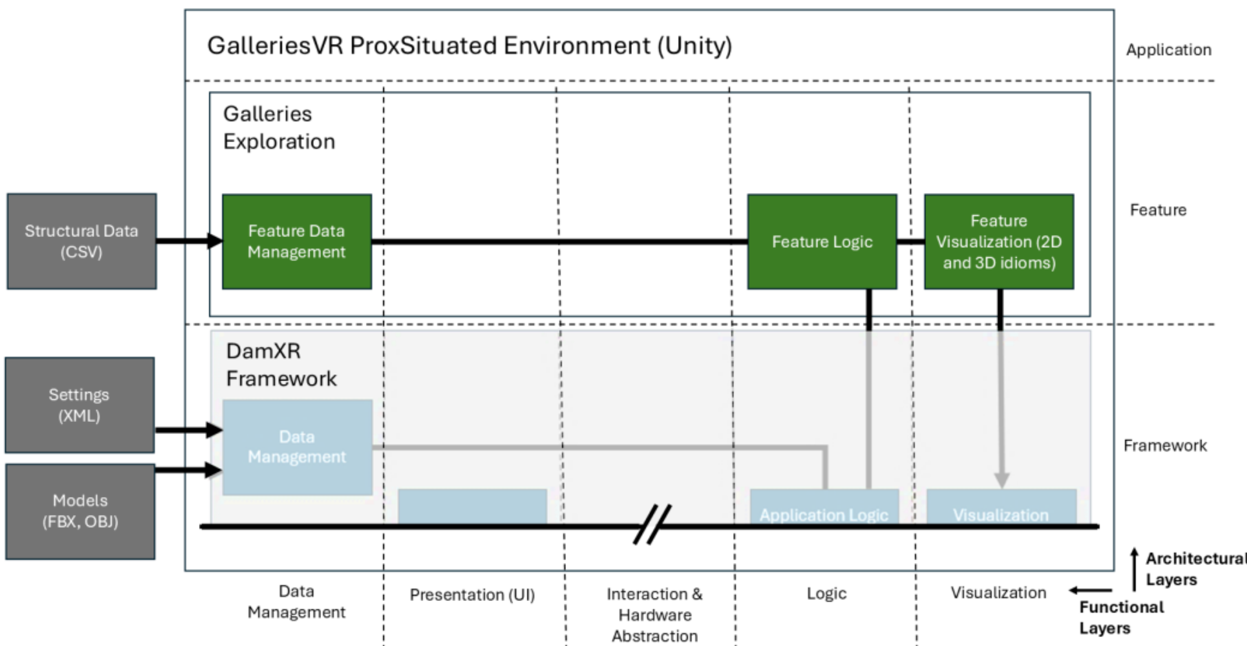


Figure 5.17: GalleriesVR architecture and its integration with the *DamXR* framework.

We also configured specific settings, such as the position and orientation of the accelerometer network sensors. Because, in this case, all the sensors were located along the same path inside the galleries, we opted to use local coordinates referenced by a notable point in the left margin gallery entrance.

There are three relevant modules at the feature level: data management, logic, and visualization. The structural accelerations dataset is initially loaded and parsed at the feature data management module. The feature logic module computes the derived measures needed to represent the accelerogram idioms. The computed measures are then used in the feature visualization module to render the 2D idioms in floating panels that can be activated by the user while inside the galleries by selecting a specific accelerometer.

In *GalleriesVR* virtual environment, users are initially placed inside the dam inspection galleries. These were modeled with a higher level of visual detail to offer users a realistic experience (Figure 5.18). They can use the controller's joystick (or the keyboard and mouse for the PC mode) to move throughout and explore the several branches and bifurcations. When they are near an accelerometer, they can select it using a selection ray coming out of the right controller.

(a) The model of the galleries

(b) The actual galleries

Figure 5.18: The galleries models built for *GalleriesVR* used a high level of visual detail, with photographic textures and high polygon count for smoother shapes, which made it possible to reproduce (a) the real galleries in the *Cabril Dam* (b) with high fidelity (Soares [149])

Users are shown a floating panel with a 2D line chart representing the most recent accelerogram when an accelerometer is selected. The chart can be panned and zoomed using the controllers (Figure 5.19).

The application also uses the frameworks' built-in gesture-activated wrist menu for activating the UI main menu. In this menu, users can select a specific date on which they want to visualize structural acceleration data.

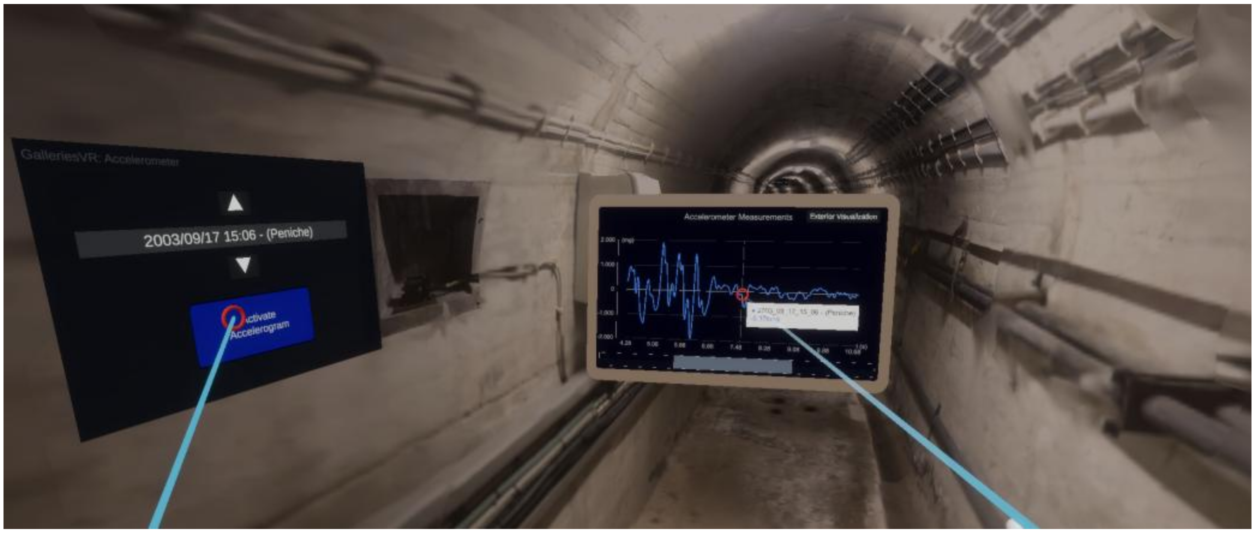


Figure 5.19: Selecting a seismic event date using the UI and visualizing the corresponding accelerogram in a floating panel (Soares [149]).

5.11.2 An application to flood data visualization

Dams are fundamental infrastructures for maintaining the hydrological balance at local and regional levels. They can efficiently regulate the volume of water that flows between hydrological basins, making them fundamental instruments in the prevention and attenuation of floods.

In that scope, a relevant task of dam safety control (one that falls outside the structural domain) is to assess the impact of the dam operation on the downstream populations. Flood prediction models, simulation, and visualization tools are very important for that.

In this context, we set to implement *FloodVR* , a *proxsituated* application for visualizing the impact of floods resulting from dam peak discharges. We wanted to understand the challenges and possibilities of using dam safety control *proxsituated* environments for analyzing data in a domain other than the structural.

The *FloodVR* application should allow users to fly above the terrain located downstream of the *Cabril Dam* (which was once again used as a case study) and visualize which areas present the most significant risk of being flooded in the event of dam peak discharges. It also should allow the visualization of the impact of floods in urban areas for each individual building.

To that extent, we used the *DamXR* framework large terrain rendering functionality for abstracting the representation, in the virtual environment, of the terrain surrounding the *Cabril Dam*. *FloodVR* 's virtual environment also includes a second, smaller dam (the *'Bouçã' Dam*) and the representation of the buildings that make up a village located downstream

(‘*Dornes*’).

We first wanted to define the main settings of the application within the *DamXR* framework. We decided to restrict the operation of the application to two modes: VR and PC. In the scope of locomotion, we chose the egocentric option for VR and the exocentric one for PC.

The architecture for the final solution of *FloodVR* and its integration with the *DamXR* framework is illustrated in Figure 5.20. At the framework level, the models of both the dam structures, the corresponding occlusion meshes, the several versions of the terrain (with distinct levels of detail), and models of ‘*Dornes*’ landmarks are loaded to the data management module. At this level, we also configured the general settings of the experience, like the modes used, the locomotion characteristics, the UI structure, and the initial positions of the user and models inside the virtual environment.

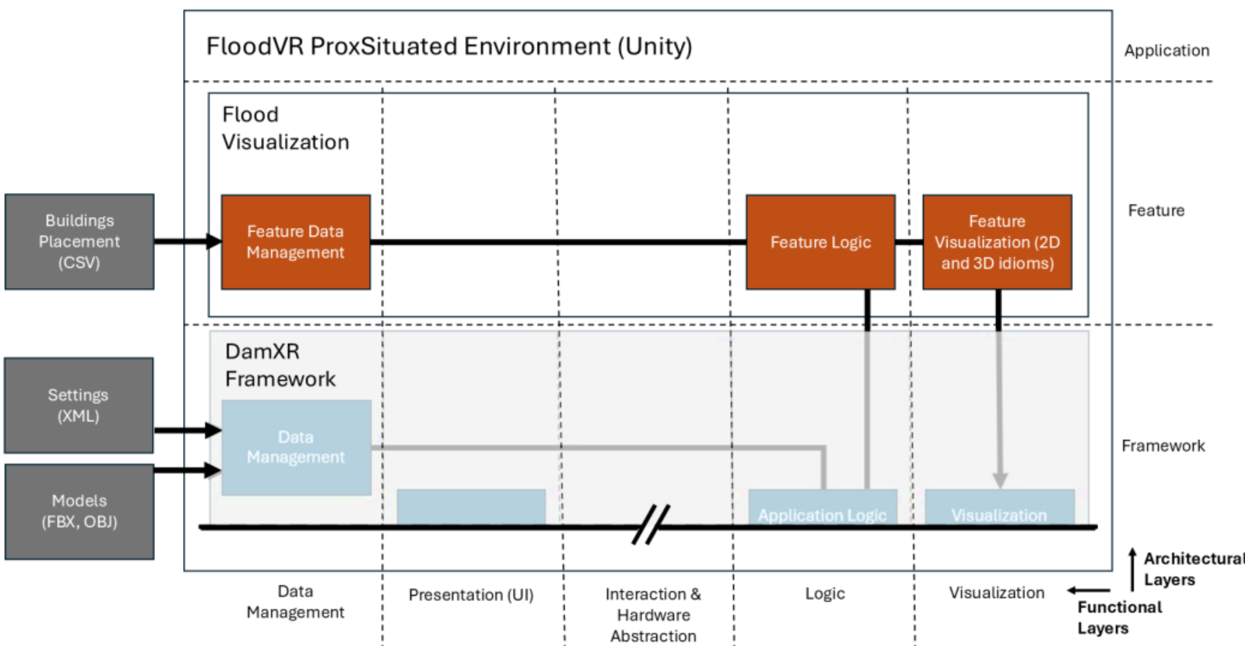


Figure 5.20: *FloodVR* architecture and its integration with the *DamXR* framework.

For both dams (*Cabril* and *Bouçã*) the reservoirs representations were carried out using *DamXR* framework reservoir water occlusion functionality. For that purpose, reservoir-specific settings like the increments used for water plane level variation occlusion were also defined.

There are three relevant modules at the feature level: data management, logic, and visualization. The placement coordinates and orientation of buildings that make up the ‘*Dornes*’ downstream village are initially loaded and parsed at the feature data management module.

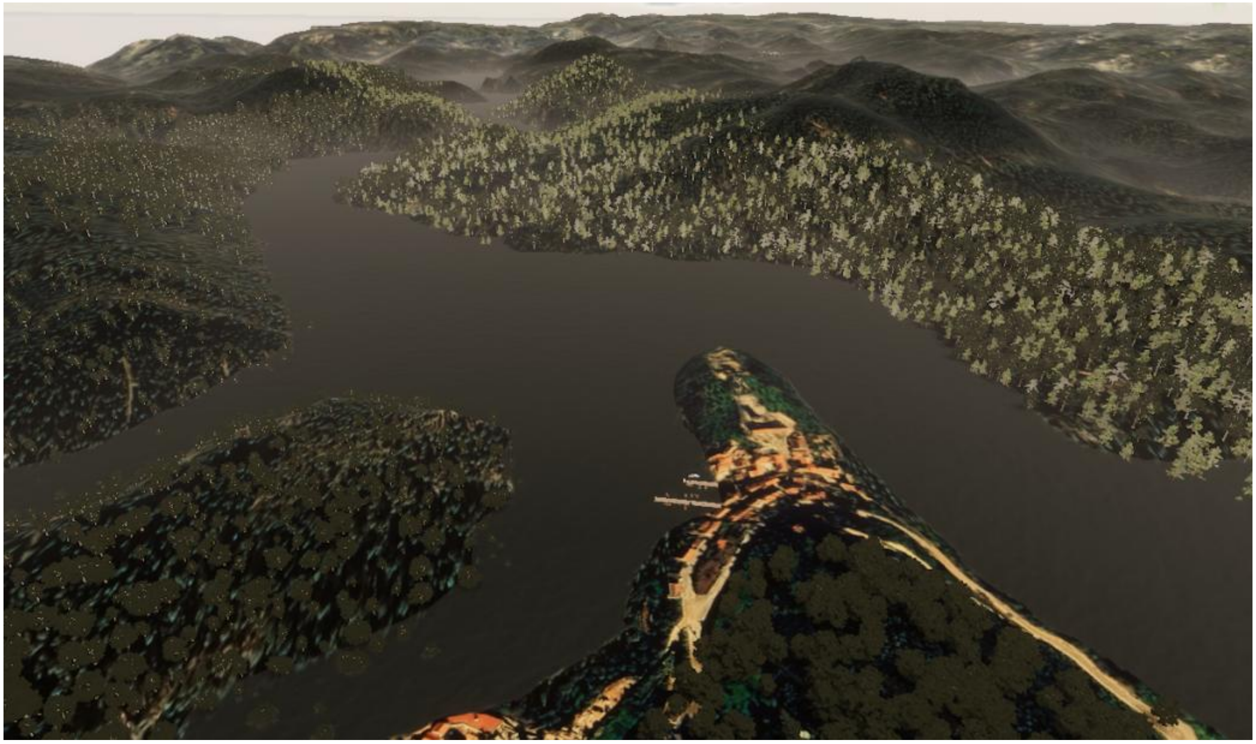
The feature logic module is responsible for three very relevant tasks. The first is the procedural generation of the various generic building layouts in '*Dornes*.' The buildings are then positioned according to the coordinates previously loaded to the feature data management module.

The second important task the feature logic module addresses is the runtime computation of terrain height so that the representation of heatmaps over the terrain (Figure 5.21), representing flood risk, can be carried out at the feature visualization module.

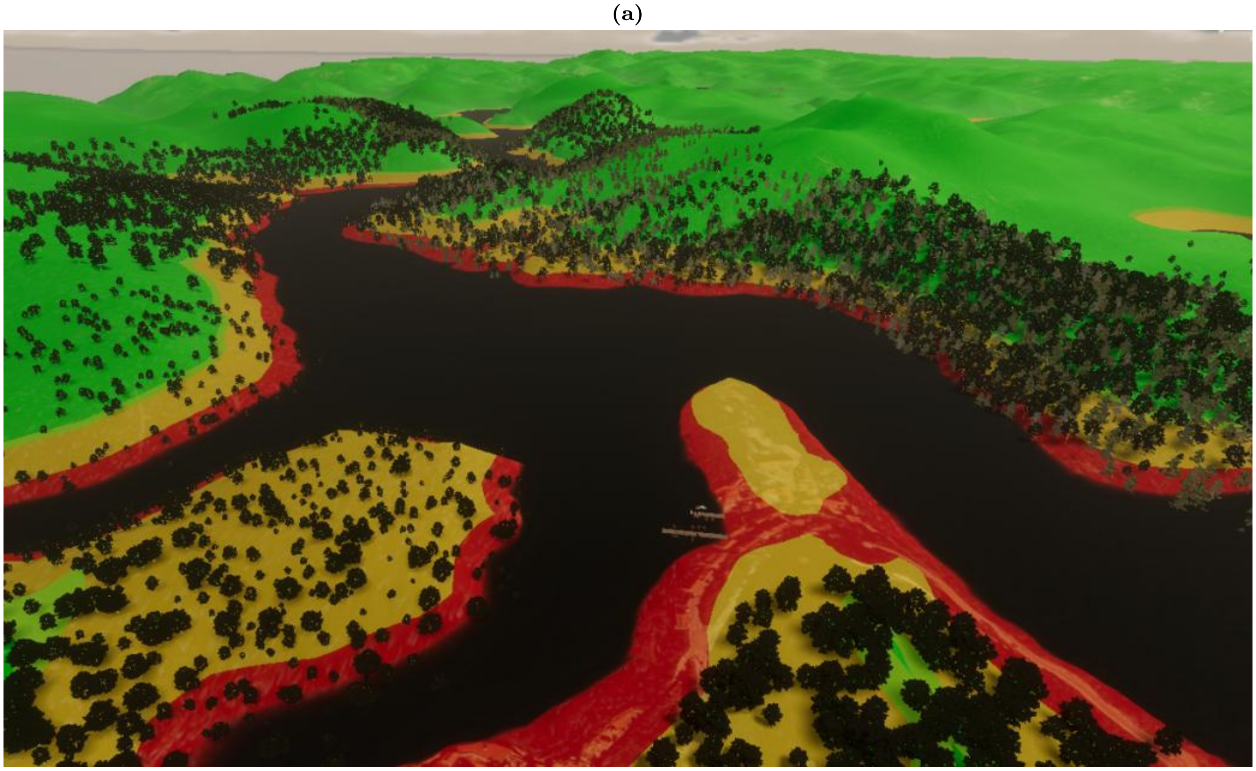
The third important task is the runtime comparison of terrain and building height with the water level to compute the submersion percentage of each building for the current water level. The colors of each building are then dynamically changed according to this submersion percentage in the feature visualization module.

In the *FloodVR* virtual environment, users are initially placed in front of the *Cabril Dam* structure. They can access the main functionalities of the application using the *DamXR* frameworks' gesture-activated wrist UI menu. This UI allows users to regulate the water levels of three different reservoirs: the upstream reservoir of the *Cabril Dam*, the upstream reservoir of the *Bouçã Dam*, and the reservoir in which the village of *Dornes* is located. The UI also allows users to toggle between flood risk heatmaps represented over the terrain and the urban submersion percentage visualization (Figure 5.22).

In addition to smooth (continuous) locomotion *FloodVR* also uses teleportation. However, instead of the 'point to teleport' mechanism, the application activates teleportation through buttons in the UI (*e.g.,* 'Teleport to *Cabril Dam*', 'Teleport to *Dornes* Village').

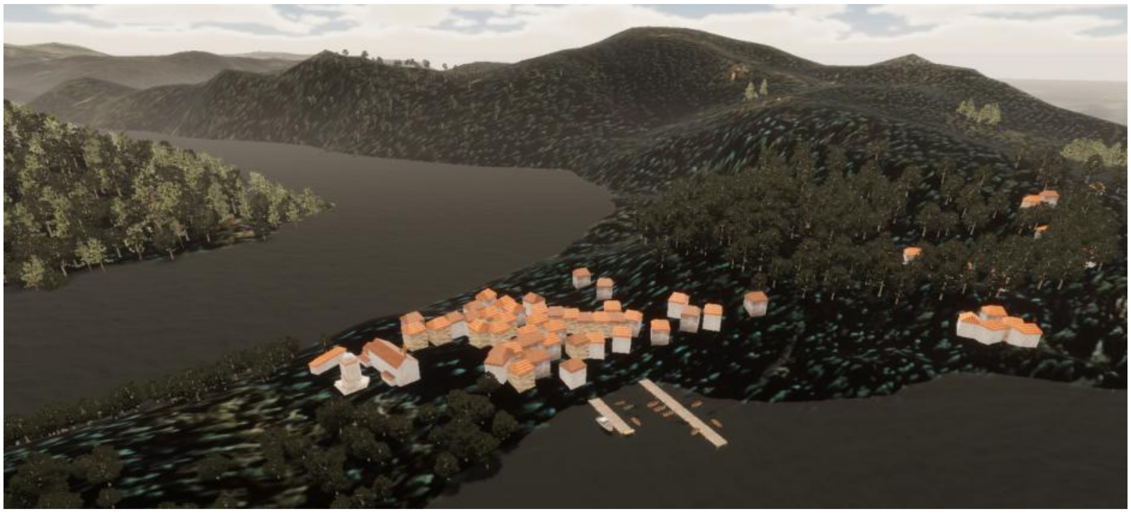


(a)

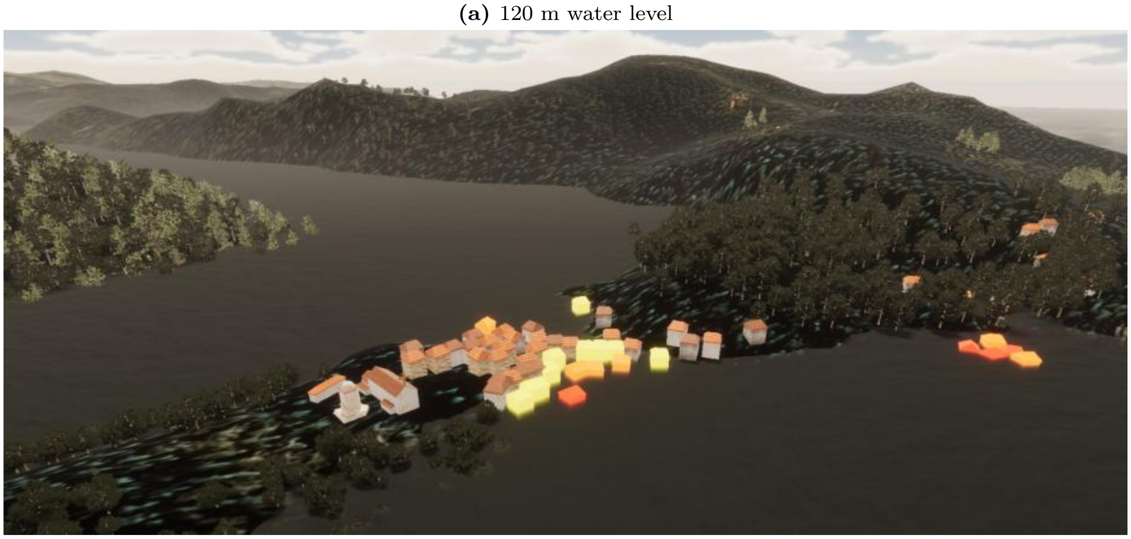


(b)

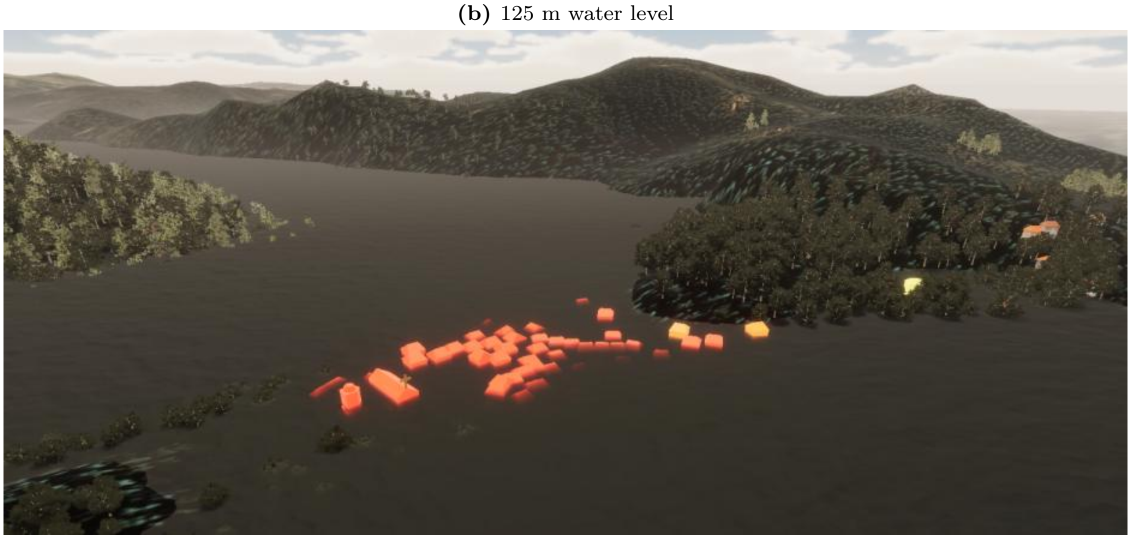
Figure 5.21: A heatmap (b) superimposed to the large terrain model (a) depicting the relative risk of flooding in the event of dam peak discharges (Pinto [123]).



(a) 120 m water level



(b) 125 m water level



(c) 128 m water level

Figure 5.22: Color coded visualization of the impact of floods in urban areas for each individual building at the *Dornes* village at different water levels (Pinto [123]).

Chapter 6

User Study

To address the proposed research questions, we tested the *DamXR* displacements visualization application[1] with a group of domain experts, which performed a set of specific analysis tasks. The broader objective of the experiment was to understand if immersive environments could offer tangible advantages in dam safety control data analysis tasks (Section 1.2). A narrower, more specific set of objectives was also defined. In particular, we wanted to understand how XR-enabled methods compared with more conventional methods in dam safety control analysis tasks (RQ1). Within the XR scope, we also wanted to compare the analysis performance of the two most widespread technologies: AR and VR (RQ2). A third specific objective was to understand if and how the visual detail of the physical referent representation influenced the analysis performance (RQ3). A fourth and final specific objective was to compare the performance of two different levels of data spatial indirection (RQ4) within the same environment: directly over the physical referent model using 3D idioms and at a certain distance from the physical referent model, using 2D idioms (with similar characteristics to its 3D counterparts) represented within floating panels.

6.1 Methodology

The *DamXR* application was evaluated through a user study. The study was sanctioned by the Ethics Committee at IST and the Data Protection Officer at INESC-ID (Annex C). In that scope, informed consent was obtained from the participants prior to conducting the experiments.

[1]For simplification, in this chapter, and from this point forward, this application will be referred to simply as '*DamXR* application'. Not to be confused with the '*DamXR* framework', which supported the development of the '*DamXR* application' and the other two applications described in Section 5.11.

6.1.1 Participants

The participants were domain experts consisting of engineers and technicians with prior experience in the dam safety control domain. Recruitment of participants for the study was done directly with the CDD at LNEC. The participants in the experiment were selected based on two criteria:

1. They had to be engineers or technicians with previous experience in the safety control of dams;
2. They had to be familiar (use in the last year in their professional activity) with conventional computing devices (such as desktop or laptop PCs);

The research team then scheduled a session at a specific date and time for the participants to enter the experiment.

When selecting the participants, the following representativeness criteria were also taken into account:

1. Academic level: The participation of professionals involved in dam safety control who had different academic levels was promoted;
2. Context of activity: The participation of professionals who work in different contexts of dam safety control (*e.g.,* observation, applied geodesy) was promoted;
3. Gender: A balanced participation of professionals of different genders was promoted.

While a balanced distribution of participants across the academic levels and context of activity was somehow attained, the study lacked balanced gender participation, as we will see further. Nevertheless, this unbalance is representative of the inherent gender gap in the engineering domain ([31], [166], [167]).

6.1.2 Materials

The hardware setup included a desktop PC with a 24-inch 2D monitor, keyboard, and mouse for running the *DamXR* application in PC mode (Figure 6.1 left). These PC specifications mimicked the ones found in the typical workstation at the CDD at LNEC. The specifications included an *Intel Xeon E5-2683 v3 @ 2.00GHz* processor, 16 GB DDR4 RAM, and an *Nvidia GeForce GTX 1070 8 GB* graphic card.

For running the *DamXR* application in the AR and VR modes, a *Meta Quest 3* XR headset with 128 GB of internal storage was used (Figure 6.1 right). This headset is compatible with both AR and VR modes. It is capable of stereoscopic color passthrough with

Figure 6.1: The desktop PC, monitor keyboard and mouse used in the experiment for running the *DamXR* application in the PC mode (left) and the *Meta Quest 3* XR headset used in the experiment for running both the *DamXR* application AR and VR modes (right).

full occlusion using depth mapping[2]. The participants were provided with disposable face masks to wear beneath the XR headset. These masks aimed to minimize direct contact between the skin and the headset.

While the *DamXR* application also supports hand tracking for user interaction, we opted for using the controllers for this experiment. This option aimed to reduce the learning curve during the tests, as most users were likely more familiar with some type of controller-based interaction than with the gesture-based option. Controllers also offered more standardized inputs, namely in what concerns the buttons pressed, offering more consistent comparisons across participants and modes.

For assessing user experience across the distinct modes tested, we used a 10-question standard System Usability Scale (SUS) [18], [100] questionnaire, employed to obtain single reference scores regarding the usability of the prototype as a whole and also each of its modes: PC, AR and VR. Participants filled out one of these questionnaires for each of the modes. While filling out the questionnaires might have been fatiguing for users, it allowed for a consistent comparison of user experience across modes.

The questions used a five-level *Likert scale* [87] for agreement (1: strongly disagree and 5: strongly agree). Half of the questions used positive phrasing, and the other half negative to reduce response bias (Table B.3).

SUS is a widely used and validated instrument for measuring perceived usability, providing a concise, standardized usability score that enables benchmarking and comparison across systems [18]. However, SUS focuses primarily on system usability. To further understand the specifics of the distinct modes tested, we aimed to capture a broader set of user experience

[2]The *Meta Quest 3* headsets' specs: https://www.meta.com/quest/quest-3/

dimensions, such as immersiveness, clarity, and perceived effort — aspects that SUS alone does not capture.

Standard user experience questionnaires (like the *User Experience Questionnaire* (UEQ) [82], the *NASA Task Load Index* (NASA-TLX) [63], or the *Post-Study System Usability Questionnaire* (PSSUQ) [136]) are ideal for subsets of user experience aspects. However, none of them fully captures the set of user experience dimensions that we considered relevant for our system. Moreover, while it would have been possible to use a combination of standardized questionnaires, such an approach would have significantly increased the time required for each participant, making it unfeasible given the time constraints of the testing sessions.

As a result, we used a 10-question non-standard user experience questionnaire, with questions targeting specific aspects/attributes. These questions used a consistent rating scale and were derived from existing items of validated questionnaires, namely the previously mentioned ones. This questionnaire was not intended to produce a single user experience score for benchmarking against other systems. Instead, we aimed to assess individual user experience dimensions that were relevant for the system under evaluation. Because participants filled out one of these questionnaires for each of the three modes (PC, AR and VR), the individual attributes could then be compared across modes as we will see further ahead.

The following attributes (Table 6.1) were addressed: immersiveness, engagement, satisfaction, perceived effort, data clarity, intuitiveness, user focus, comfort, feedback, and post-use impact. The mapping of each question with the attribute we intended to target is presented in Table B.2.

We considered this set of attributes to be relevant for an overall characterization of the experience differences between modes in the scope of RQ1 and RQ2. Each attribute highlighted an aspect where AR, VR, and PC modes would likely diverge. The magnitude of that divergence would assert how the use of each mode affected participants' interaction, perception, and overall effectiveness.

In particular, the reasons for choosing questions addressing these particular attributes were the following:

1. Immersiveness – Measuring immersiveness helps quantify how much XR enhances the feeling of 'being there' compared to traditional screen-based experiences. Based on the intrinsic characteristics of each mode, it was likely the immersiveness of VR>AR>PC. In addition to determining the magnitude of differences, the question concerning this attribute would help us validate this relation in our application area.

2. Engagement – Like immersiveness, a higher engagement is almost a defining feature of XR. XR modes, due to their differences in interaction, involvement, and depth of

the experience, are expected to be more engaging than PC. However, this attribute would help us validate whether that assumption would hold for our analysis-focused environment.

3. Satisfaction – We wanted to know if the added complexity brought by analytics features would introduce usability challenges that would be detrimental to an enjoyable experience in XR.
4. Perceived Effort – We wanted to gauge if the burden brought by the learning curve for immersive interactions in XR in users with low prior experience with XR was substantial, in comparison with a visualization modality they were very familiar with (PC).
5. Data Clarity – Despite the data representation being the same across the three tested modes, we wanted to assess the possible differences in readability and the ability to interpret information brought by the different devices and visualization modalities.
6. Intuitiveness – We wanted to determine how natural the user interactions were with the XR modes.
7. User Focus – This attribute would allow us to assess how efficient the UI was for each mode in keeping the users focused on the tasks at hand.
8. Comfort – Measuring comfort would help us understand if XR physical demands would outweigh its benefits.
9. Feedback – We wanted to know if participants' perception of the UI responsiveness and feedback remain unaltered despite the differences in visualization modalities and input modes (controllers and mouse-and-keyboard).
10. Post-Use Impact – We wanted to assess how memorable and emotionally impactful the experience was across modes.

The questions used a five-level *Likert scale* for agreement (1: strongly disagree and 5: strongly agree). Similarly to the previously mentioned and more general purpose SUS, half of the questions of this more specific questionnaire used positive phrasing and the other half negative in order to reduce response bias.

For collecting the social and demographic characteristics of the participants, we used a sociodemographic data questionnaire which also included their prior experience with technology (including with XR/immersive environments). The questions concerned participants' age, profession, gender, education level, professional experience in the field of dams and previous experience with extended reality technologys. In addition we also used a final feedback

#	Attribute	Description
1	Immersiveness	The degree to which participants felt immersed in the application
2	Engagement	The level of interest, motivation, and active involvement
3	Satisfaction	The overall sense of fulfillment, pleasure, or positive feeling derived from the experience
4	Perceived Effort	The participant's feeling of how much effort they had to exert
5	Data clarity	The participant's feeling of how well the data was communicated
6	Intuitiveness	The degree to which the interface and interactions felt natural, self-explanatory, and easy to learn
7	User focus	The degree to which the participants' attention and mental concentration remained directed toward the tasks.
8	Comfort	The extent to which the experience was free from physical discomfort, strain, or unpleasant after-effects
9	Feedback	The quality, clarity, and timeliness of the systems' reactions to participants' inputs
10	Post-use impact	The positive lasting effects or impressions the experience left on the participant

Table 6.1: User experience attributes and descriptions

form with open-ended questions to gather qualitative insights into users' impressions, challenges, and suggestions, for complementing the quantitative data recorded.

We also wanted to assess if the participant's perception of the usefulness and practicability of XR technologies had changed after experimenting with the *DamXR* application. In particular, we wanted to address the perception of the usefulness of XR in dam safety control and the practicability of XR devices in that activity. Additionally, we wanted to understand the change in perception regarding specific aspects like the visual detail, data representation type, and the use of adjacent elements to the physical referent (terrain and other landscape items).

With that objective, we used a seven-question questionnaire (Table B.1) with a five-level *Likert scale* for agreement (1: strongly disagree and 5: strongly agree). Some questions used positive phrasing and others negative to reduce response bias. We asked the participants to complete the questionnaire at the beginning of the test session before they interacted with the prototype and again at the end of the test session after they had completed the proposed tasks with the prototype.

We instrumented the application to log real-time data related to user interaction with the models and interfaces. We developed a specialized module named *DamXR Telemetry* for that purpose. This module allows interaction logs to be stored locally on the device where the *DamXR* application is being run. It also enables the secure transmission of the logs to a remote server. These remote logs can be visualized in near-real-time by the test team using a complementary desktop application (Figure 6.2 (c)). This desktop application communicates with the remote server using a client-server architecture. With the desktop application, the test team can send commands via the remote server to the devices where the *DamXR* application is being run on (a PC or a XR headset). This mechanism was fundamental for alternating between test modes and variants during the experiments.

To enable easier control of the different stages of the experiment by the test team using the desktop *DamXR Telemetry* visualization application, we modified a wireless keyboard with key tags corresponding to the main stages/modes of the experiment. This set of keys corresponded to shortcuts for activating the training mode, recording task success or failure, or activating specific variants of each task, among others (Figure 6.2 (d)).

The experiment setup also included a camera for video recording of the user when wearing the XR headset (Figure 6.2 (a)). A secondary visualization device was also used to allow the test team to observe what the participant was seeing while wearing the headset. This device (a smartphone) used *Meta Horizons*' *Android* app live casting feature[3] for mirroring the view of the participants inside the immersive environment (Figure 6.2 (b)).

In summary, during the sessions, the following data was collected:

1. Task performance: task completion time, task completion (whether the participant finished the assigned task at all before the cutoff time), and task success (whether the participant gave the correct answer);

2. Sociodemographic data and previous experience with technology;

3. Opinion data: participants' opinions regarding the usability, usefulness, and suitability of the prototypes.

[3]Casting to a screen with *Meta Quest*: https://www.meta.com/help/quest/articles/in-vr-experiences/oculus-features/cast-with-quest/

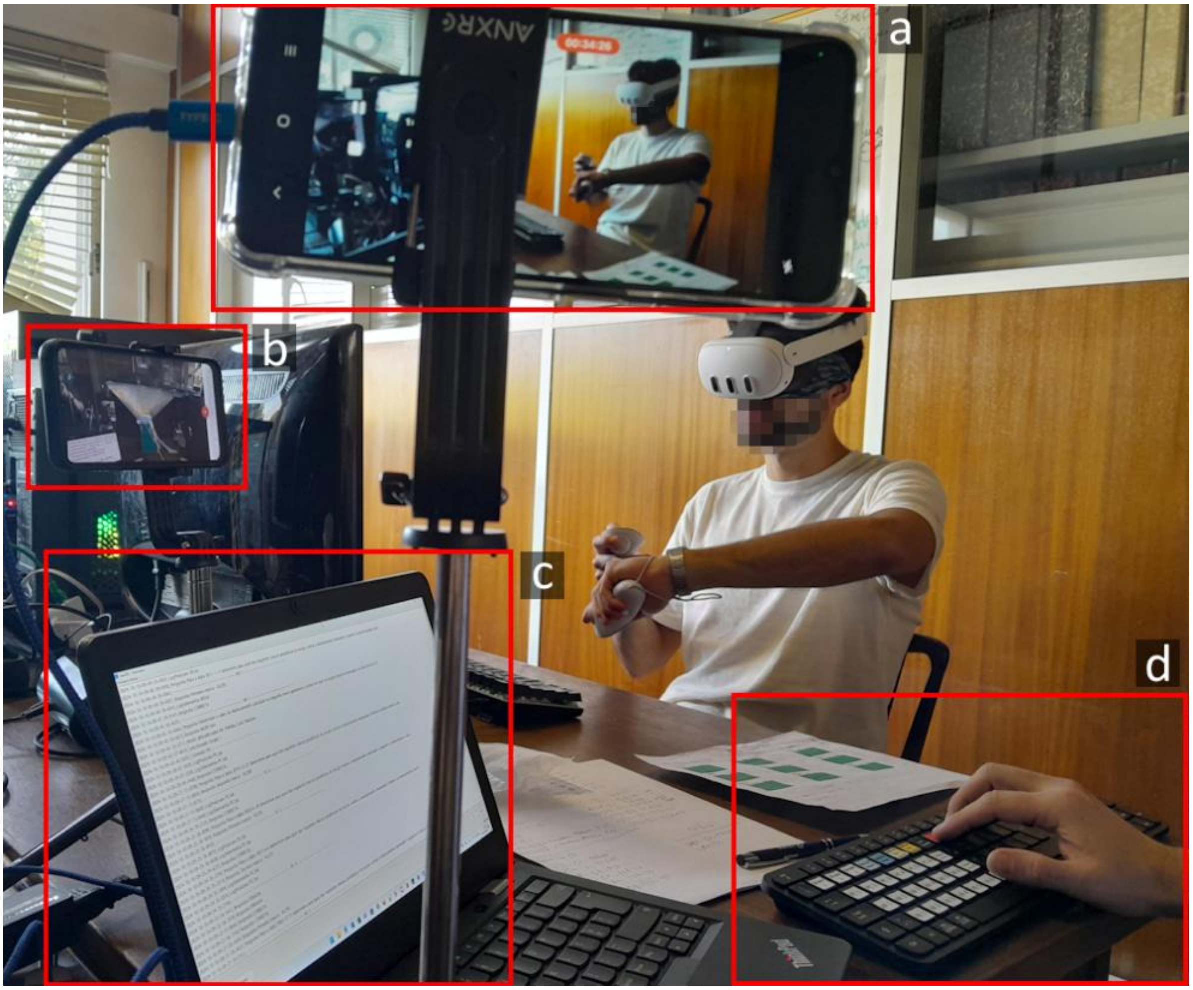


Figure 6.2: The experiment setup included a camera for video recording of the user movements (a), a screen for showing the test team what the participant is seeing while wearing a headset (b), a desktop computer running *DamXR Telemetry* (c) and wireless keyboard, operated by the test team, customized with shortcut keys for alternating between modes and test stages (d). The visible parts of the subjects' faces were blurred/pixelated to further protect their privacy.

6.1.3 Tasks

The tasks were designed in close collaboration with domain experts at LNEC (who were not part of the group participating in the user tests to ensure an independent assessment). They resulted from informal interviews and direct observation of the activity at the CDD at LNEC. This collection of information was carried out throughout the development of the thesis work and allowed an iterative refinement of the relevance of the tasks. As such, in this experiment, we adopted user tasks that are both representative of everyday dam safety control analysis tasks carried out by engineers and technicians and suitable to answer our research questions.

The three tasks vary in complexity: lower, medium, and higher complexity. Their specific scope is described in Table 6.2. The tasks text presented to the participants is shown in Table A.1.

Task	Objective	Complexity
TA	Identifying the name of a geodetic mark at a specific position in the dam	Lower
TB	Determining the displacement value recorded at a specific geodetic mark and a certain date	Medium
TC	Comparing the recorded and estimated displacement values between two geodetic marks at a certain date	Higher

Table 6.2: Experiment tasks, their objectives and level of complexity

Tasks TA and TB were carried out for the three distinct modes of the *DamXR* application, *i.e.*, AR, VR and PC (Figure 6.3) with fixed visual detail and data indirection characteristics. Task TC was carried out for the three distinct modes, for distinct visual detail levels (using higher visual detail - textures and lower visual detail - *flat shading*) and for different data indirection characteristics (low spatial data indirection - data overlapped to the referent and high spatial data indirection - represented in floating panels containing charts). As such, TC entails four variants: High Visual Detail and Low Spatial Data Indirection (HDLI), Low Visual Detail and Low Spatial Data Indirection (LDLI), High Visual Detail and High Spatial Data Indirection (HDHI), and Low Visual Detail and High Spatial Data Indirection (LDHI). The characteristics of the task variants are detailed in Table A.2. The set of six task variants (synthesized in Table 6.3) for each of the three modes totals 18 task rounds for each participant.

Variant	Description
TA	Task A using 3D idioms directly over the referent and textured model
TB	Task B using 3D idioms directly over the referent and textured model
TC-HDLI	Task C using 3D idioms directly over the referent and textured model
TC-LDLI	Task C using 3D idioms directly over the referent and flat-shaded model
TC-HDHI	Task C using 2D idioms in panels and textured model
TC-LDHI	Task C using 2D idioms in panels and flat-shaded model

Table 6.3: Experiment task variants and descriptions

This structure was devised to achieve the proposed goals in a feasible, manageable test session duration (under 60 minutes for each participant). As such, with TA and TB we intended a higher level comparison between XR modalities and the baseline (desktop PC with conventional 2D screen). With TC, we intended a lower-level comparison of the characteristics of the analysis environment for each visualization modality.

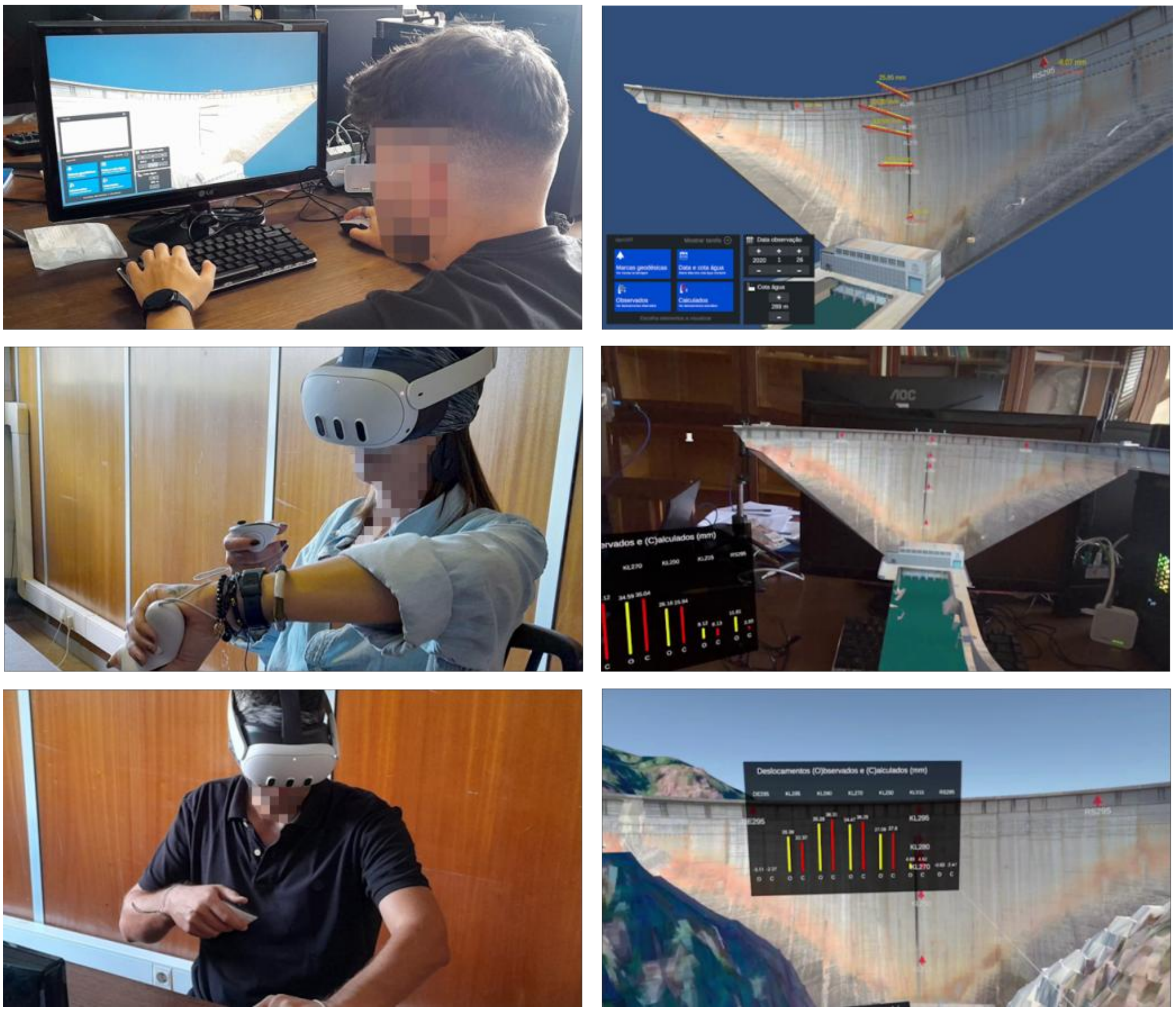


Figure 6.3: The three modes of the *DamXR* application tested in the experiment: PC (top-left and top-right images), AR (middle-left and middle-right images) and VR (bottom-left and bottom-right). The images on the left show the physical interaction with the prototype, and the images on the right are screenshots of what is visualized in each mode. The top-left image is of a test team member demonstrating the use of the PC mode, while the middle-left and bottom-left images are of actual participants carrying out tasks with the *DamXR* application during the experiment. The visible parts of the subjects' faces were blurred/pixelated to further protect their privacy.

Because we wanted to measure each of the subjects under every variant/condition (within-subjects testing), we adopted a *Latin Square Method* approach for changing conditions' order throughout the experiment [33] to minimize order effects/bias.

6.1.4 Procedures

The study was carried out at the CDD facilities at LNEC. While initially programmed to be carried out at INESC-ID, because participants were more willing to take the tests at LNEC, this location was chosen instead. Such preference was because the entirety of participants were part of LNEC staff. The room used for the experiments at LNEC offered similar spatial conditions to the initially planned room at INESC-ID. The room at LNEC was also closer to the environment characteristics that users could find in the real world during their everyday work.

The room was actively being used by the LNEC staff for everyday work but was freed up for the exclusive purpose of conducting our tests. Like many of the CDD rooms, it was equipped with a series of workstations where engineers and technicians did their everyday work. Apart from not having co-workers in the room, it can be considered an adequate experimental environment for reproducing real-world conditions (Figure 6.4).

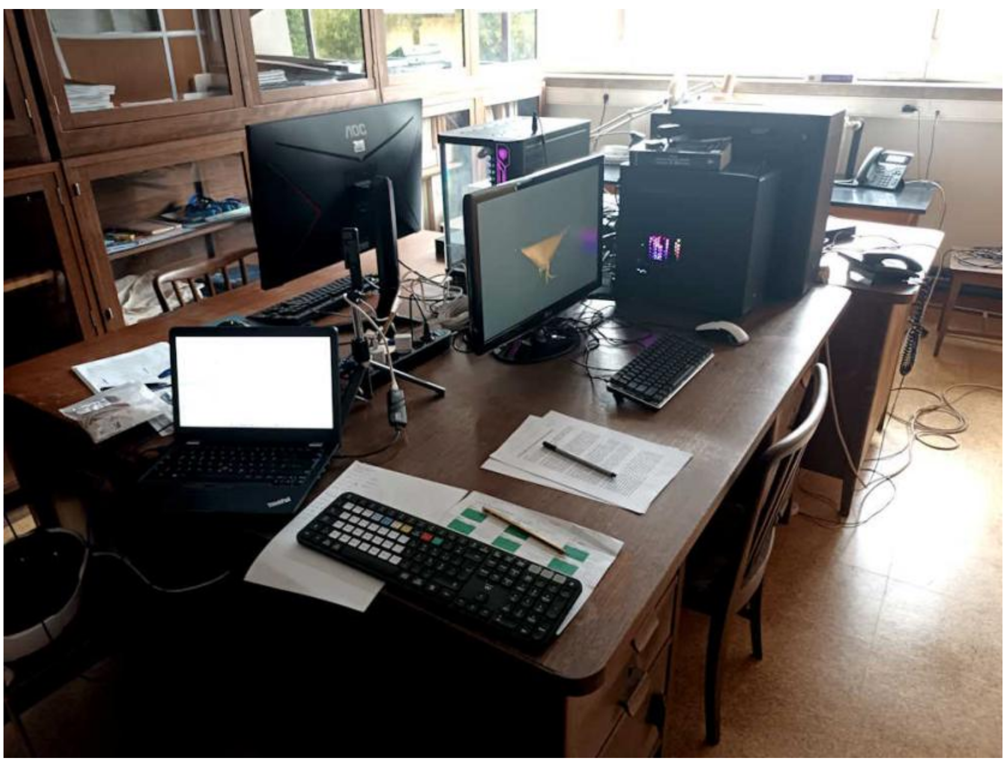


Figure 6.4: The room used for the experiment is part of the actual workplace at LNEC. It has a series of workstations where engineers and technicians work.

At the beginning of each test session, after a brief introduction to the experiment's objectives, the participants were asked to read and sign an informed consent regarding their participation in the tests. Next, the participants were asked to complete the sociodemographic data questionnaire, followed by the XR technologies perception questionnaire. After completing this initial stage, the participants were invited to try out the prototype. This experimentation stage allowed the familiarization of the participants with the different XR technologies used and the prototype's distinct modes and features.

After the tryout stage, the participants were asked to perform a series of three types of tasks with each of the three modes (AR, VR and PC) of the *DamXR* application and with each of the graphic fidelity (textured and *flat shading*) and data representation (3D directly over the referent and 2D in panels) variations. Throughout the experiment, they were encouraged to verbalize their actions by adopting the *Think Aloud Method* [48].

We asked the users to perform the tasks in a seating posture because we wanted to condition the XR interaction aspects to the physical space effectively available in a real dam engineering office. This posture is also the one they adopt for working in the office workstations in their everyday work. In that context, and on the one hand, a more physically active standing posture would devitalize the relevance of the experience by not taking into account the real operating conditions. On the other hand, adopting different postures for different modes would hinder the comparability of XR conditions with the more traditional PC baseline mode (which is necessarily associated with a seated posture).

In the task performance stage, the tasks were initially presented to the user inside the application. This task presentation was done using a static interface panel, floating in an empty canvas, that contained the text of the task and a button with the caption 'Start the task' ('*Iniciar tarefa*') (Figure 6.5, left). This mechanism was devised due to the fact that in the VR mode, the user cannot see the real world, and as such, the use of other mechanisms to show the task to the participant (*e.g.,* showing a paper with the task text before putting on the headset) would not be practical. The users pressing the start task button made elements of the immersive environment (*i.e.* referent, terrain, and menus) visible to the participant and determined the beginning of the task itself.

We also devised a mechanism for users to consult the task text during the task performance. That mechanism was activated through a selectable option ('show task') in the main menu. The participants were then presented with a sliding panel showing the task text, which allowed them to remember in case they forgot the goal and details of the task (Figure 6.5, right). This reminder was essential for tasks that involved entering a specific date or analyzing multiple geodetic marks.

Each task began with the participant located at the same coordinates of the virtual space

Figure 6.5: In the task performance stage, the tasks were initially presented to the user in a floating panel inside the application itself (left). The participant could also consult the task text during the task performance (right). Screenshots (cropped) of a participant's view while performing a task in the VR, non-textured mode

and was considered finished as soon as the participant said the answer out loud. To prevent misunderstandings regarding the actual answer (due to the participants adopting the *Think Aloud Method*, as previously mentioned), participants were asked to say the response (a value or a position) preceded by the prompt 'The answer to the task is...' ('*A resposta à tarefa é...*').

After completing the tasks, the participants were asked to fill out the SUS questionnaire, the non-standard user experience questionnaire, the feedback form, and again the XR technologies perception questionnaire, in that order.

6.2 Results

The participants were domain experts, consisting of 31 engineers and technicians with prior experience in the dam safety control domain. They were all part of LNEC staff. The set of participants included Civil Engineers (65%), Geographic Engineers (3%), Geological Engineers (3%), and Field and Lab Technicians (32%). Additionally, 55% of the engineers were also researchers.

The participants had an age range of 32-68 years old and an average age of 50 years old. Concerning the gender distribution, 77% of participants were male and 23% female. A very significant portion of the participants were highly educated, with 61% holding a PhD degree and 19% with a Master of Science (MSc) or equivalent (*i.e. pre-Bologna 'Licenciatura'* degree). The remaining 19% of participants were holders of a high school diploma.

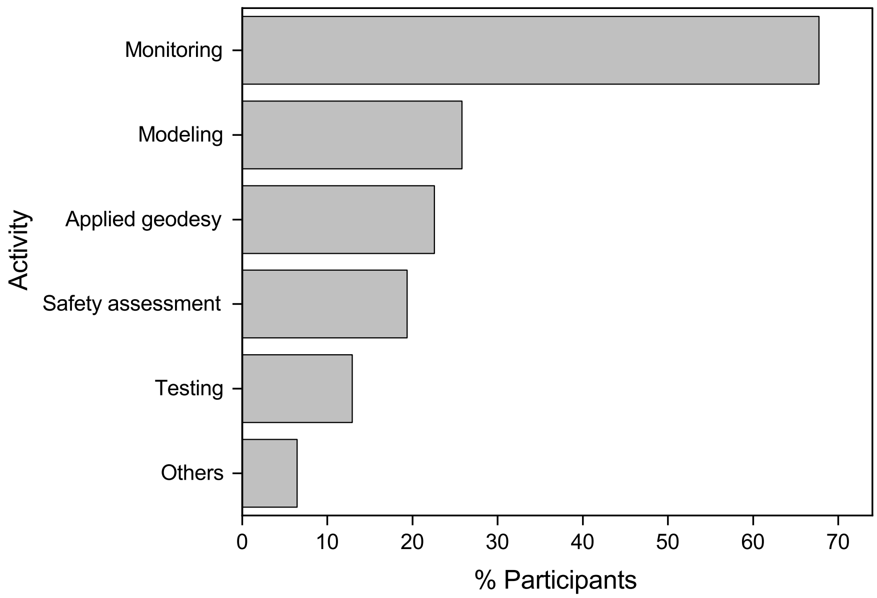


Figure 6.6: Dam safety control activities the participants were involved in (some were involved in multiple activities).

The participants had significant experience in dam safety control activities, and most of them were seasoned professionals with an average of approximately 21 years of experience in the field. Concerning the physical context where they primarily carried out their activity, 68% did it mostly *off-site*, in the office, and 10% did it mostly *on-site*, in the field. Additionally, 22.6% of participants carried out their activity in the office and the field for equal periods.

Regarding the type of dam safety control activities the participants were involved in, mostly (68%) were engaged in dam monitoring[4], 26% in dam modeling[5] and 23% in applied geodesy[6]. Participants were also involved in wider-ranging activities, such as dam safety assessment (including behavior analysis, behavior interpretation, and safety control) (19.4%), dam-related testing (13%), and other varied activities such as dam design and dam-related underground works (6.5%) (Figure 6.6).

We also surveyed the participants' habits and prior experience with using technology in the scope of their activity. The vast majority (87%) of participants used dam data visualization software tools in their everyday work. These tools were mostly (29%) *GestBarragens*, an integrated information management system for concrete dams safety control [20] and the *Microsoft Excel* spreadsheet charting features (29%). There was also significant use of *in-house*

[4] Activity framed within the Monitoring Unit ('Núcleo de Observação') at CDD at LNEC

[5] Activity framed within the Modeling and Rock Mechanics Unit ('Núcleo de Modelação e Mecânica das Rochas') at CDD at LNEC

[6] Activity framed within the Applied Geodesy Unit ('Núcleo de Geodesia Aplicada') at CDD at LNEC

developed visualization applications (19%) for that purpose. And because many of the CDD participants were both engineers and researchers, they used statistical computing and graphics tools, namely *R* (13%). They also used CAD tools (13%) and the *MATLAB* development environment for visualizing dam data (10%). To a lesser extent, the participants reported to use of Finite Element Method (FEM) tools (7%) and Geographic Information Systems (GISs) (7%). Furthermore, they used specialized simulation and 2D/3D visualization software (26%), namely *GiD* (7%), *FLAC2D* (7%), *3DEC* (3%), *Rhino* (3%), *Code_Aster* (3%) and *ParaView* (3%).

The participants were also asked about the visualization features of the software tools they used. The majority of participants (65%) use applications that allow the visualization of dam models. The remaining use applications that do not allow such visualization. Furthermore, from participants using model-visualization-capable applications, 95% stated that those applications allow the visualization of 2D models and 75% the visualization of 3D models. In addition 70% stated that the applications allow the visualization of both 2D and 3D models.

The participants were equally asked how often did they use the 2D/3D dam model visualization feature of the software tools. From the ones that use model-visualization-capable applications, 55% used this feature once a month, 25% used it daily, 10% used it weekly and 10% only used it yearly.

Concerning the devices used in their daily activity, all participants used desktop or laptop computers. Desktop computers were used by 97% of the participants, and laptop computers were used by 77% of participants. Likewise, 74% used both desktop and laptop computers concurrently. Participants also reported using smartphones (29%) and tablets (3%) in their dam safety control activities. As such, 100% of the users used 2D screen devices, with no users reporting using VR/AR headsets in their activity.

We also wanted to characterize the users in what regards their familiarity with XR technology. Many of the participants (58%) had used XR technologies before. In particular, 58% of the participants reported having used VR and 19% to have used AR before. Additionally, all the users that had contact with AR had also used VR technologies. Around 42% of the participants had never tried XR technologies.

Regarding the frequency with which they used XR, 52% of the participants used it occasionally (less than once a year). And a mere 7% reported using XR once a year. Additionally, participants were also asked about the scope in which they had used XR. Only 33% of the participants that had previous contact with XR before had used it in the scope of their activity (the others used it for different purposes than professional). And from those, 67% had used XR for 3D model visualization, 50% for data visualization, and 42% for other purposes.

Additionally, we asked the users what comfort level they experienced when using XR. We used a five-level scale for comfort, from 'very uncomfortable' to 'very comfortable'. From those who had tried XR before, 39% found their previous experiences 'very comfortable', 28% 'comfortable', 28% 'neutral' and 6% found them 'uncomfortable'. None of these participants found the previous experiences with XR to be 'very uncomfortable'.

6.2.1 Influence of display and interaction modalities

In the scope of RQ1, we wanted to understand if there were any user-experience advantages in using XR for dam data visualization compared to conventional means. For that purpose, we used the results from the SUS questionnaires mentioned in Section 6.1.

In order to have a representative measure for comparing the usability results of the two XR modes combined with the results obtained for the PC mode, we calculated the mean SUS score of AR and VR. The combined AR, VR mean SUS scores was 85.9 (M = 87.5, SD = 10.6). Such a score can be paired with a descriptive rating of 'Excellent' [9] or 'A+' (84.1 - 100) [84]. The score can also be associated with 100% accuracy based on the sample size threshold proposed by Tullis and Stetson [155].

For the PC mode, an average SUS score of 81.1 (M = 82.5, SD = 14.4) was obtained. Such a score can be paired with a descriptive rating of 'Excellent' [9] or 'A' (80.8 - 84.0) [84]. The scores difference between the XR modes and the PC indicate a slight usability advantage of the former (Figure 6.7). To understand the statistical significance of this variation of scores given by participants, a *Wilcoxon Signed-Rank Test* [177] was carried out, with a prior assessment of the distribution nonnormality (using a *Shapiro–Wilk Test* [145])[7]. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of scores, with $p < 0.031$ ($W = 297.5$, $Z = -2.156$, $r = -0{,}3872$).

To further understand the specific aspects/attributes where XR could have user-experience advantages over PC, we used the results from the non-standard user experience questionnaire mentioned in Section 6.1.

Once again, in order to have a representative measure for comparing the usability results of the two XR modes combined with the results obtained for the PC mode, we calculated the mean participants' scores of AR and VR. For the calculations, adjusted scores were used (from 0 to 4), based on the original scores given by individual participants to each attribute (from 1 to 5)[8]. To understand the statistical significance of the variations of scores given

[7] Effect sizes (r) were calculated for each comparison by dividing the *Wilcoxon* Z-value by the square root of the number of valid pairs (N), following *Rosenthal's* recommendation [137]. They should be interpreted using *Cohen's* benchmarks [28]: small (≈ 0.1), medium (≈ 0.3), and large (≥ 0.5).

[8] Because our non-standard user experience questionnaire has similarities with a standard SUS ques-

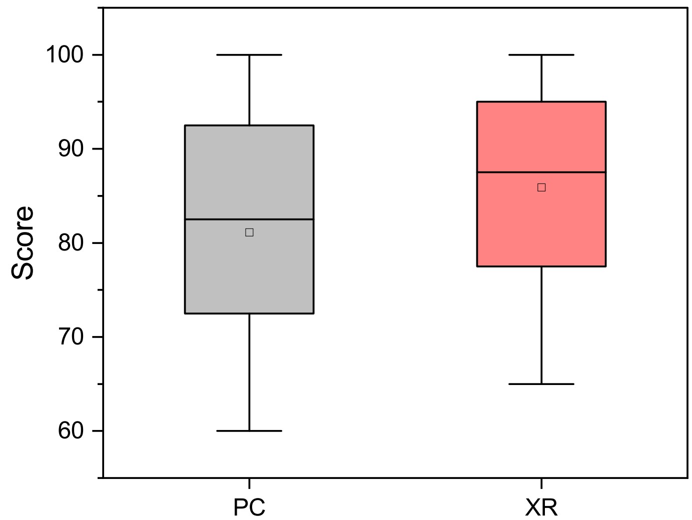


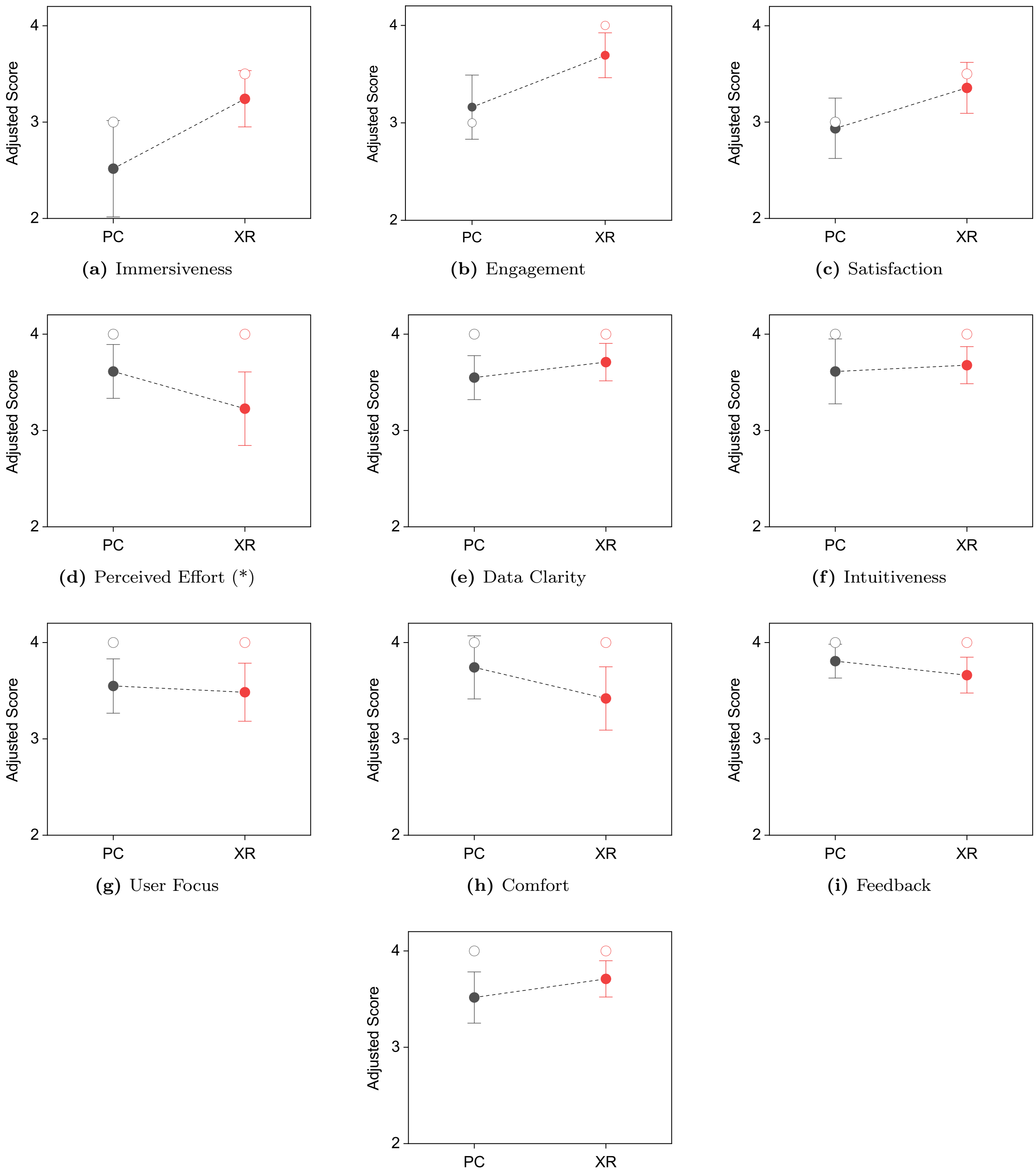
Figure 6.7: Participants' SUS scores for the PC mode and scores' mean for the XR modes (AR and VR) (vertical scale restricted for increased visibility of the differences).

by participants, *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

Regarding immersiveness, participants found the XR modes more immersive than the PC (Figure 6.8 (a)). This result was unsurprising (due to the more immersive characteristics that typically characterize XR technologies), with an average score of 3.2 (M = 3.5, SD = 0.8) for XR against 2.5 (M = 3.0, SD = 1.4) for PC. The individual VR score, 3.4 (M = 4.0, SD = 0.9), was the one that contributed more to the positive combined score of XR. The AR score was lower than for VR 3.1 (M = 3.0, SD = 0.9), but still significantly higher than the PC one. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the sets of scores, with $p < 0.010$ (W = 189.0, Z = -2.568, r = -0.4612) for XR-PC, $p < 0.004$ (W = 150.5, Z = -2.667, r = -0.4790) for VR-PC and $p < 0.044$ (W = 106.50, Z = -2.013, r = -0.3615) for AR-PC.

Participants also considered the XR modes more engaging, with scores of 3.7 (M = 4.0, SD = 0.6) for the XR modes and 3.2 (M = 3.0, SD = 0.9) for the PC mode (Figure 6.8 (b)). The VR mode was once again the highest scored of the three modes, with a result of 3,8 (M = 4.0, SD = 0.7) for engagement, followed by AR, with a score of 3.6 (M = 4.0, SD = 0.7). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the sets of scores, with $p < 0.002$ (W = 171.5, Z = -3.143, r = -0.5645) for XR-PC, $p < 0.001$ (W = 173.0, Z = -3.381, r = -0.6072) for VR-PC and $p < 0.016$ (W = 99.0, Z = -2.398, r = -0.4307) for AR-PC.

tionnaire (namely in what regards the alternation between positively and negatively phrased questions) we adopted a procedure that is in line with what is used when calculating SUS [18] scores. This procedure aims to re-code scores to ensure consistency across all questions before the summation and final scoring.



(a) Immersiveness (b) Engagement (c) Satisfaction

(d) Perceived Effort (*) (e) Data Clarity (f) Intuitiveness

(g) User Focus (h) Comfort (i) Feedback

(j) Post-Use Impact (**)

Figure 6.8: Adjusted scores for the PC and XR modes for the multiple user experience attributes considered (vertical scale restricted for increased visibility of the differences). (*) For the perceived effort attribute (d), a higher value represents a lower perceived effort. (**) The post-use impact attribute (j) refers to a positive impact on participants.

The XR modes were considered the most satisfactory, with a satisfaction score of 3.4 (M = 3.5, SD = 0.7) (Figure 6.8 (c)). The PC mode received a significantly lower score of 2.9 (M = 3.0, SD = 0.9). Moreover, from the XR modes, VR was once again the preferred, achieving a score of 3.4 (M = 4.0, SD = 0.8). AR was not very much behind, with a score of 3.3 (M = 3.0, SD = 0.8). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the sets of scores, with $p < 0.020$ (W = 247.0, Z = -2.325, r = -0.4176) for XR-PC, $p < 0.040$ (W = 185.5, Z = -2.051, r = -0.3684) for VR-PC and $p < 0.041$ (W = 128.5, Z = -2.045, r = -0.3673) for AR-PC.

Concerning perceived effort, the PC mode was the one with a higher score (corresponding to a lower perceived effort), achieving a result of 3.6 (M = 4.0, SD = 0.8) (Figure 6.8 (d)). The XR modes were perceived by the participants to have corresponded to a higher effort, having achieved a score of 3.2 (M = 4.0, SD = 1.0). Moreover, the XR modes individually still corresponded to higher perceived efforts than PC, with AR achieving a score of 3.3 (M = 4.0, SD = 1.0) and VR a score of 3.1 (M = 4.0, SD = 1.1). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between PC-XR, with $p < 0.022$ (W = 68.0, Z = -2.297, r = -0.4126) and PC-VR, with $p < 0.016$ (W = 69.0, Z = -2.405, r = -0.4320). However, for PC-AR, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the two sets of scores.

XR were considered by the participants the most favorable modes for data clarity with a score of 3.7 (M = 4.0, SD = 0.5), one of the highest scores achieved across all addressed aspects (Figure 6.8 (e)). The PC mode was rated with a slighter lower score of 3.6 (M = 4.0, SD = 0.6). Regarding the individual XR modes, the AR mode achieved a score of 3.8 (M = 4.0, SD = 0.5), its highest across all addressed aspects and higher than the PC mode score. The VR achieved a very similar score to the PC mode, of 3.6 (M = 4.0, SD = 0.7). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between AR-PC, with $p < 0.021$ (W = 40.5, Z = -2.309, r = -0.4147). However, for XR-PC and PC-VR, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

The XR modes were also rated as more intuitive than the PC by participants (Figure 6.8 (f)). The average score of XR modes was 3.7 (M = 4.0, SD = 0.5), while the PC mode received a score of 3.6 (M = 4.0, SD = 0.9). The VR mode was the one that most contributed to the XR intuitiveness score, with a rate of 3.7 (M = 4.0, SD = 0.5). However, it was closely followed by AR, which received a score of 3.6 (M = 4.0, SD = 0.6). Nevertheless, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

Concerning the capability of the user to stay focused within the tasks objectives, PC received the highest score, 3.6 (M = 4.0, SD = 0.8), ahead of the XR modes, which were scored 3.5 (M = 4.0, SD = 0.8) (Figure 6.8 (g)). The AR and VR contributed in equal parts for this result, with a score of 3.5 (M = 4.0, SD = 0.8) for the former and 3.5 (M = 4.0, SD = 0.9) for the latter. However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

In what regards the feeling of comfort and physical well-being, participants reported being more comfortable using the PC mode, with a score of 3.7 (M = 4.0, SD = 0.9) (Figure 6.8 (h)). The XR modes received a lower score of 3.4 (M = 4.0, SD = 0.9). From the XR modes, AR was the highest positive contributor for the XR modes result, with a score of 3.6 (M = 4.0, SD = 0.8). The VR mode achieved a comfort score of 3.2 (M = 4.0, SD = 1.1). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between PC-XR, with $p < 0.014$ (W = 70.0, Z = -2.470, r = -0.4436) and PC-VR $p < 0.010$ (W = 52.5, Z = -2.584, r = -0.4641). However, for PC-AR, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

The PC mode also achieved the highest result for the feedback attribute, with a score of 3.8 (M = 4.0, SD = 0.5) (Figure 6.8 (i)). The XR modes received a lower score of 3.7 (M = 4.0, SD = 0.5). The AR mode, with a score of 3.7 (M = 4.0, SD = 0.5), was the mode with the highest contribution for the XR mode score, in contrast with VR which achieved a score of 3.6 (M = 4.0, SD = 0.6). However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

Finally, in what concerns post-use impact, the XR modes achieved a higher score - 3.7 (M = 4.0, SD = 0.5) - than the PC mode, which scored 3.5 (M = 4.0, SD = 0.7) (Figure 6.8 (j)). Moreover, AR was once again the mode with the highest contribution for the XR modes result, with a score of 3.8 (M = 4.0, SD = 0.5). The VR mode was scored 3.6 (M = 4.0, SD = 0.7) by participants concerning the post-use impact attribute. The results, however, do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

In addition to the participants' opinions, we also registered objective metrics while they were carrying out the tasks. These metrics aimed at supporting the analysis of performance for the distinct modes of the prototype with multiple task variants. A relevant set of these metrics included the task completion time, task completion (whether the participant finished the assigned task at all before the cutoff time), and task success (whether the participant gave the correct answer).

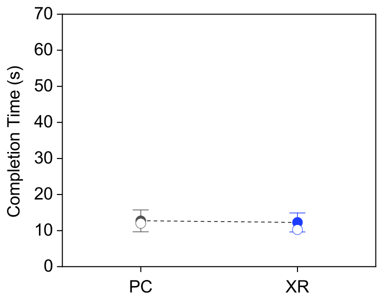
In order to have a representative measure for comparing the completion time results of the two XR modes combined with the results obtained for the PC mode, we calculated the mean participants' completion time of AR and VR. To understand the statistical significance of the variations of times between participants, *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

For the PC mode, an average completion time of 217.2 seconds across the sums of all task times (TA, TB, and TC variants) for each participant was obtained. A slightly higher result was obtained for XR, with an average of sums of times (average of AR and VR total completion times) of 219.5 seconds. To understand the statistical significance of this completion time variation of scores, a *Wilcoxon Signed-Rank Test* was carried out, with a prior assessment of the distribution nonnormality (using a *Shapiro–Wilk Test*). The results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of completion times across participants.

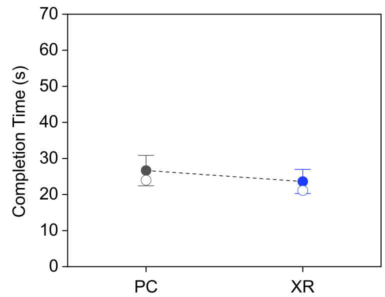
We also wanted to address the differences in completion times across specific tasks. The average completion times, medians, and standard deviations were calculated for each task for both PC and XR modes. For TA, an average completion time of 12.7 seconds (M = 12.0, SD = 8.2) was registered for the PC mode, while a lower averaged time of 12.3 seconds (M = 10.2, SD = 8.4) was measured for XR. Regarding TB, the PC mode had an average completion time of 26.6 seconds (M = 24.0, SD = 11.5), again substantially higher than the value registered for the XR mode, of 23.6 seconds (M = 19.3 SD = 12.4). The same tendency was registered for TC-HDLI, with an average completion time of 44.1 seconds (M = 41.6, SD = 15.9) for PC and 26.4 seconds (M = 17.8, SD = 21.3) for XR. Likewise, TC-LDLI scored an average completion time of 41.0 seconds (M = 39.8, SD = 15.2) for PC and 35.1 seconds (M = 31.9, SD = 14.9) for XR.

With a tendency in the opposite direction, the task TC-HDHI, recorded an average completion time of 50.7 seconds (M = 48.8, SD = 20.9) for the PC mode, a value lower than the registered for the XR mode, of 59.9 seconds (M = 46.0, SD = 27.9). The TC-LDHI task had the same tendency direction but with an even larger gap between PC, with an average completion time of 42.0 seconds (M = 41.2, SD = 8.9) and the 62.2 seconds (M = 53.7, SD = 22.5) registered for XR. These differences between the average completion times for PC and XR are illustrated in Figure 6.9.

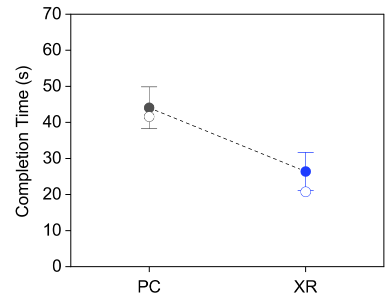
The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between PC and XR modes for tasks TC-HDLI, TC-LDLI, TC-HDHI and TC-LDHI (higher complexity). However, for task TA (lower complexity) and TB (medium complexity), the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores. The results of



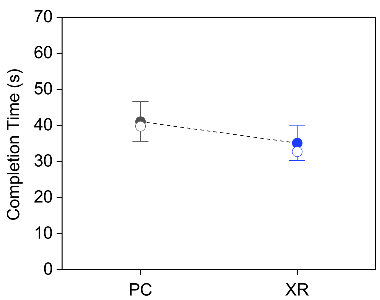
(a) TA



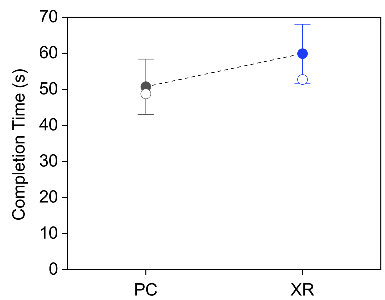
(b) TB



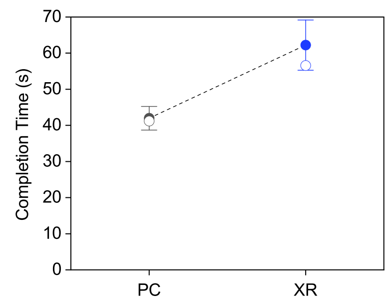
(c) TC-HDLI



(d) TC-LDLI



(e) TC-HDHI



(f) TC-LDHI

Figure 6.9: Completion times for the PC and XR modes, for each of the tasks performed by participants.

Wilcoxon Signed-Rank Tests for differences between the completion times of modes PC and XR for each task are presented in Table 6.4.

Task	W	Z	r	p	Sig.
TA	225.0 (+)	-0.451	-0.0810	0.652	-
TB	188.0 (+)	-1.176	-0.2112	0.240	-
TC-HDLI	43.0 (+)	-4.017	-0.7215	< 0.001	✓
TC-LDLI	140.0 (+)	-2.116	-0.3800	0.034	✓
TC-HDHI	138.0 (−)	-2.156	-0.3872	0.031	✓
TC-LDHI	8.0 (−)	-4.703	-0.8447	< 0.001	✓

Table 6.4: *Wilcoxon Signed-Rank Tests* for differences between the completion times of modes PC and XR for each task. W represents the raw test statistic based on positive (+) or negative ranks (-), Z the standardized test statistic and r the effect size.

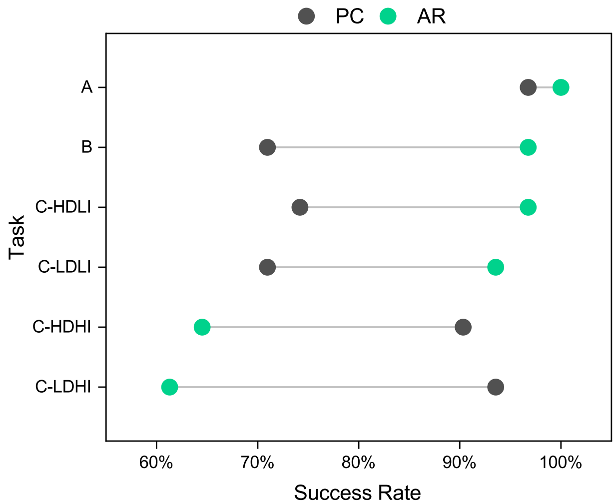
Regarding task completion, the experiment accounted for a 100% completion rate, with all the participants finishing the task before the time limit. However, task success varied substantially across the PC and XR modes. For analyzing task success results, and because we were working with binary repeated measures, we applied *McNemar's Tests* for comparisons.

Table 6.5 presents the success rates for each task and mode. For the PC mode, an average success rate of 82.8% ± 5.4% across all tasks (TA, TB, and TC variants) was obtained. In comparison, XR modes obtained a higher average success rate, of 84.4% ± 3.7%, with AR and VR registering, respectively, 85.5% ± 5.1% and 83.3% ± 5.4% average success rates.

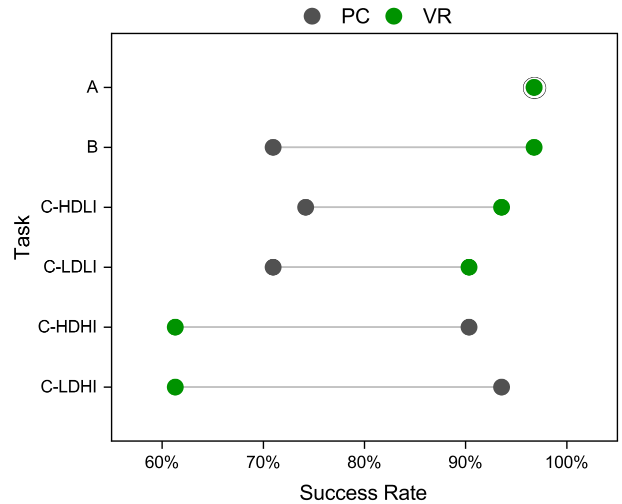
Mode	Task	Success	Rate	95% CI (approx)
PC	TA	30/31	97%	(91%, 100%)
	TB	22/31	71%	(55%, 87%)
	TC-HDLI	23/31	74%	(59%, 90%)
	TC-LDLI	22/31	71%	(55%, 87%)
	TC-HDHI	28/31	90%	(80%, 100%)
	TC-LDHI	29/31	94%	(85%, 100%)
AR	TA	31/31	100%	(90%, 100%)
	TB	30/31	97%	(91%, 100%)
	TC-HDLI	30/31	97%	(91%, 100%)
	TC-LDLI	29/31	94%	(85%, 100%)
	TC-HDHI	20/31	65%	(48%, 81%)
	TC-LDHI	19/31	61%	(44%, 78%)
VR	TA	30/31	97%	(91%, 100%)
	TB	30/31	97%	(91%, 100%)
	TC-HDLI	29/31	94%	(85%, 100%)
	TC-LDLI	28/31	90%	(80%, 100%)
	TC-HDHI	19/31	61%	(44%, 78%)
	TC-LDHI	19/31	61%	(44%, 78%)
XR	TA	61/62	98%	(95%, 100%)
	TB	60/62	97%	(92%, 100%)
	TC-HDLI	59/62	95%	(90%, 100%)
	TC-LDLI	57/62	92%	(85%, 99%)
	TC-HDHI	39/62	63%	(51%, 75%)
	TC-LDHI	38/62	61%	(49%, 73%)

Table 6.5: Success rates for each task.

The comparison between success rates of PC vs. AR and PC vs. VR for the different tasks is represented in Figure 6.10. To assess the statistical significance of the differences between success results, separate *McNemar's Tests* were carried out to compare the two above-mentioned pairs. *Odds Ratios* (OR) were also calculated for each pair to estimate the direction and strength of performance shifts between conditions [116]. For pairs with zero discordant cases, the *Haldane–Anscombe Correction* [7], [62] was applied to obtain stable OR estimates. The results of these tests are presented in Table 6.6.



(a) PC-AR



(b) PC-VR

Figure 6.10: Comparison between success rates of PC vs. AR and PC vs. VR for the different tasks (horizontal scale restricted for increased visibility of the differences).

Comparison	Task	N	*OR*	*p*	Sig.
PC-AR	TA	31	0.333	1.000	-
	TB	31	0.158	0.021	✓
	TC-HDLI	31	0.067	0.016	✓
	TC-LDLI	31	0.176	0.039	✓
	TC-HDHI	31	4.200	0.039	✓
	TC-LDHI	31	21.000	0.002	✓
PC-VR	TA	31	1.000	1.000	-
	TB	31	0.059	0.008	✓
	TC-HDLI	31	0.077	0.031	✓
	TC-LDLI	31	0.200	0.070	-
	TC-HDHI	31	4.600	0.022	✓
	TC-LDHI	31	7.667	0.006	✓

Table 6.6: *McNemar's Tests* results for differences between the task success for modes PC-AR and PC-VR.

6.2.2 Influence of reality modality

In the scope of RQ2, we wanted to understand the differences between AR and VR in the scope of user-experience advantages. For that purpose, we used the results provided by the 10-question standard SUS questionnaire mentioned in Section 6.1.

For the AR mode, an average SUS score of 85.1 (M = 87.5, SD = 12.1) was obtained. Such a score can be paired with a descriptive rating of 'Excellent' [9] or 'A+' (84.1 - 100) [84]. Regarding the VR mode, an average SUS score of 86,7 (M = 87.5, SD = 10.3) was obtained.

Such a score can be paired with a descriptive rating of 'Excellent' [9] or 'A+' (84.1 - 100) [84]

The scores difference between the AR modes and the VR indicate a usability advantage of the latter (Figure 6.11). To understand the statistical significance of this variation of scores given by participants, a *Wilcoxon Signed-Rank Test* was carried out, with a prior assessment of the distribution nonnormality (using a *Shapiro–Wilk Test*). The results, however, do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

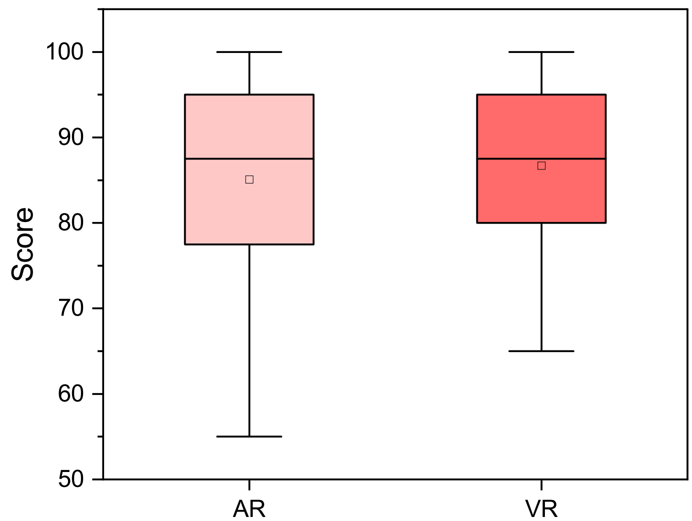
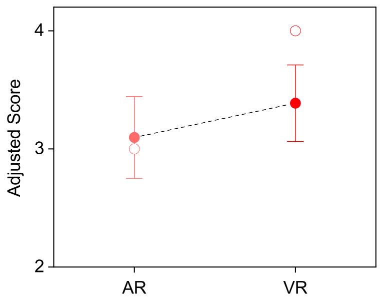


Figure 6.11: Participants' SUS scores for the AR and VR modes (vertical scale restricted for increased visibility of the differences).

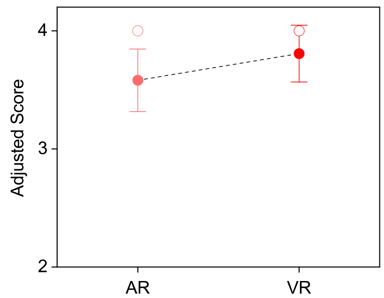
While the difference in AR and VR SUS scores was not conclusive, we wanted to find out if there were specific usability aspects/attributes where significant differences existed. With that objective, the results of the 10-question non-standard user experience questionnaire, targeting the ten specific usability attributes mentioned in Section 6.1, were used. To understand the statistical significance of the variations of scores given by participants, *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

Regarding immersiveness, participants found, as expected, the VR mode to be more immersive than AR (Figure 6.12 (a)). For the immersiveness attribute, the VR mode achieved a score of 3.4 (M = 4.0, SD = 0.9), while AR scored a substantially lower 3.1 (M = 3.0, SD = 0.9). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of individual scores, with $p < 0.047$ (W = 72.5, Z = -1.990, r = -0.3574).

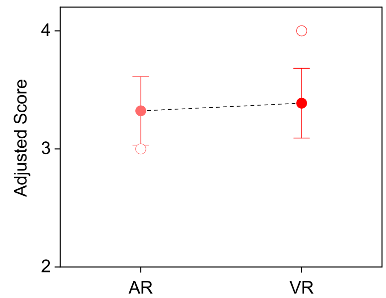
In what concerns engagement, once again, participants considered VR to be a more engaging mode than the AR mode (Figure 6.12 (b)). While VR was rated with a score of



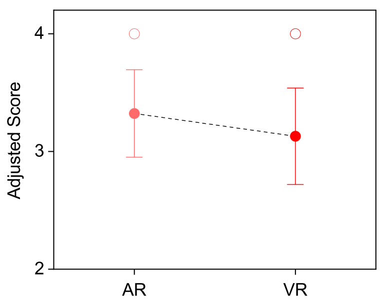
(a) Immersiveness



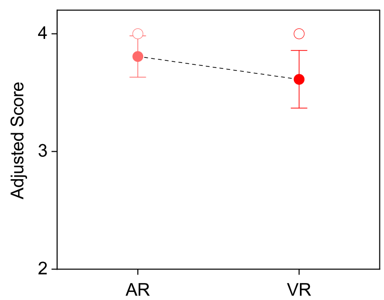
(b) Engagement



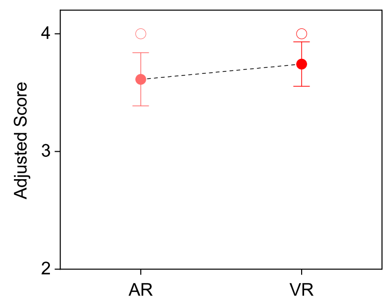
(c) Satisfaction



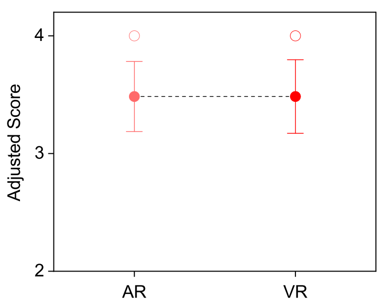
(d) Perceived Effort (*)



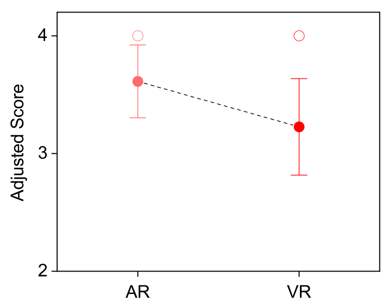
(e) Data Clarity



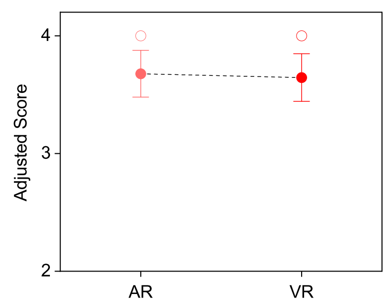
(f) Intuitiveness



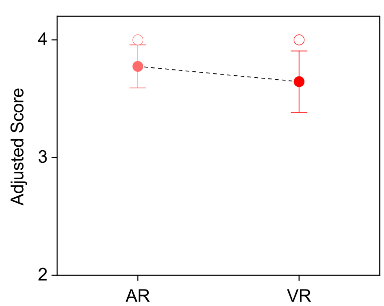
(g) User Focus



(h) Comfort



(i) Feedback



(j) Post-Use Impact (**)

Figure 6.12: Adjusted scores for the AR and VR modes for the multiple user experience attributes considered (vertical scale restricted for increased visibility of the differences). (*) For the perceived effort attribute (d), a higher value represents a lower perceived effort. (**) The post-use impact attribute (j) refers to a positive impact on participants.

3.8 ($M = 4.0$, $SD = 0.7$), AR received a score of 3.6 ($M = 4.0$, $SD = 0.7$). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of individual scores, with $p < 0.035$ ($W = 32.0$, $Z = -2.111$, $r = -0.3791$).

For the satisfaction attribute, participants scored the VR mode with 3.4 ($M = 4.0$, $SD = 0.8$) and the AR mode 3.3 ($M = 3.0$, $SD = 0.8$) (Figure 6.12 (c)). These scores indicate a more satisfactory experience in the VR mode than in the AR mode. However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

Concerning the perceived effort, participants associated the AR experience with a lower perceived effort than the VR mode (Figure 6.12 (d)), scoring the AR mode with 3.3 ($M = 4.0$, $SD = 1.0$) and the VR mode with 3.13 ($M = 4.0$, $SD = 1.1$) (a higher score corresponding to a lower perceived effort). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of individual scores, with $p < 0.034$ ($W = 15.0$, $Z = -2.121$, $r = -0.3809$).

Participants also reported a preference for AR over VR in what concerns data clarity (Figure 6.12 (e)). Indeed, the AR mode scored 3.8 ($M = 4.0$, $SD = 0.5$) for the data clarity attribute, while VR scored 3.6 ($M = 4.0$, $SD = 0.7$). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of individual scores, with $p < 0.034$ ($W = 31.5$, $Z = -2.121$, $r = -0.3809$).

In what regards the intuitiveness attribute, the participants scored the VR with 3.7 ($M = 4.0$, $SD = 0.5$) and the AR mode with 3.6 ($M = 4.0$, $SD = 0.6$) (Figure 6.12 (f)). However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

The attribute reflecting the capability of the user to stay focused within the task objectives had a very similar preference for both VR, with a score of 3.5 ($M = 4.0$, $SD = 0.9$) and AR, with a score of 3.5 ($M = 4.0$, $SD = 0.8$) (Figure 6.12 (g)). However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

A feeling of higher comfort and physical well-being was paired more often with AR. Indeed, for the comfort attribute, the participants scored 3.6 ($M = 4.0$, $SD = 0.8$) for the AR mode and 3.2 ($M = 4.0$, $SD = 1.1$) for the VR mode (Figure 6.12 (h)). The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of individual scores, with $p < 0.017$ ($W = 59.0$, $Z = -2.377$, $r = -0.4269$).

The feedback and responsiveness attribute had very similar scores in both modes (Figure 6.12 (i)). Participants scored VR with 3.7 ($M = 4.0$, $SD = 0.6$) and AR with 3.7 ($M = 4.0$, $SD = 0.5$). However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

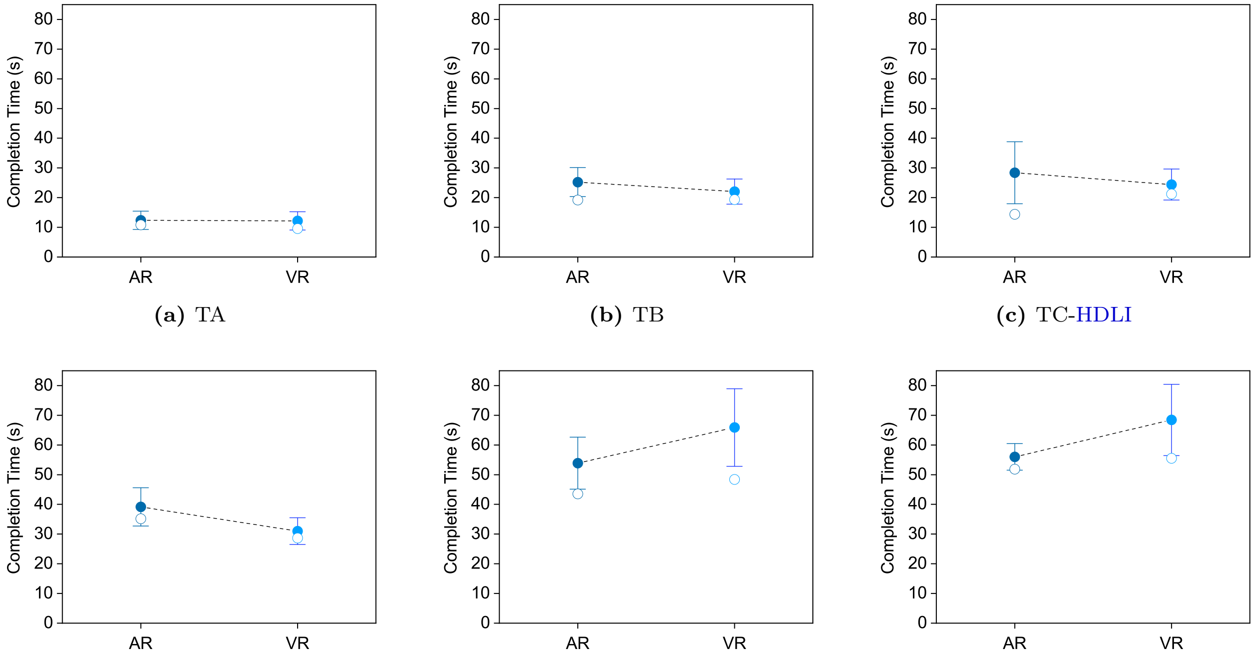
Finally, post-use impact had a more favorable score for the AR mode than VR (Figure 6.12 (j)). Participants scored the former with 3.8 (M = 4.0, SD = 0.5) and the latter with 3.7 (M = 4.0, SD = 0.7). However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores.

In addition to the opinion of participants, objective metrics for the AR and VR modes were also registered. These metrics are aimed at supporting the analysis of performance for these two modes of the prototype with multiple task variants. A relevant set of these metrics included the task completion time, as well as task completion and task success. To understand the statistical significance of the variations of times between participants, once again *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

For the AR mode, an average completion total time of 215.0 seconds across the sum of all task times (TA, TB, and TC variants) for each participant was obtained. A substantially higher average completion total time of 223.9 seconds was obtained for VR. The results of a *Wilcoxon Signed-Rank Test* do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of completion times across participants.

We also wanted to address the differences in completion times across specific tasks for the AR and VR modes. The average completion times, medians, and standard deviations were calculated for each task. For TA, an average completion time of 12.4 seconds (M = 10.8, SD = 8.4) was registered for the AR mode, while a lower averaged time of 12,2 seconds (M = 9.6, SD = 8.4) was measured for VR. Regarding TB, the AR mode had an average completion time of 25.2 seconds (M = 19.2, SD = 13.3), again substantially higher than the value registered for the VR mode, of 22,0 seconds (M = 19.3, SD = 11.5). The same tendency was registered for TC-HDLI, with an average completion time of 28.4 seconds (M = 14.4, SD = 28.5) for AR and 24.4 seconds (M = 21.2, SD = 14.2) VR for VR. Likewise, TC-LDLI scored an average completion time of 39.2 seconds (M = 35.2, SD = 17.6) for AR and 31.0 seconds (M = 28.7, SD = 12.3) for VR.

With the opposite tendency, the task TC-HDHI recorded an average completion time of 53.9 seconds (M = 43.5, SD = 23.9) for the AR mode, a value lower than the registered for the VR mode, of 65.9 seconds (M = 48.4, SD = 35.6). The TC-LDHI task had the same tendency direction, with an average completion time of 56.0 seconds (M = 51.9, SD = 12.2) registered for AR and 68.4 seconds (M = 55.5, SD = 32.8) for VR. These differences between the average completion times for AR and VR are illustrated in Figure 6.13.



(a) TA **(b)** TB **(c)** TC-HDLI **(d)** TC-LDLI **(e)** TC-HDHI **(f)** TC-LDHI

Figure 6.13: Completion times for the AR and VR modes, for each of the tasks performed by participants.

With the exception of TC-LDLI, the results of *Wilcoxon Signed-Rank Tests* for differences between the completion times of modes AR and VR for each task do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the sets of scores. These results are presented in Table 6.7.

Task	W	Z	r	p	Sig.
TA	222.0 (+)	-0.510	-0.0916	0.610	-
TB	192.0 (+)	-1.097	-0.1970	0.272	-
TC-HDLI	214.0 (−)	-0.666	-0.1196	0.505	-
TC-LDLI	80.0 (+)	-3.292	-0.5913	< 0.001	✓
TC-HDHI	180.0 (−)	-1.333	-0.2394	0.183	-
TC-LDHI	164.0 (−)	-1.646	-0.2956	0.100	-

Table 6.7: *Wilcoxon Signed-Rank Tests* for differences between the completion times of modes AR and VR for each task. W represents the raw test statistic, Z the standardized test statistic and r the effect size.

The success rates for each task for the AR and VR modes were presented earlier in Table 6.5. For the AR mode, an average success rate of 85.5% ± 5.1% across all tasks (TA, TB, and TC variants) was obtained. In comparison, the VR mode obtained a lower average success rate of 83.3% ± 5.4%. The comparison between success rates of AR and VR for the different tasks is represented in Figure 6.14.

To assess the statistical significance of the differences between each task success results in the AR and VR modes, *McNemar's Tests* were carried out. However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the task success results for the two modes.

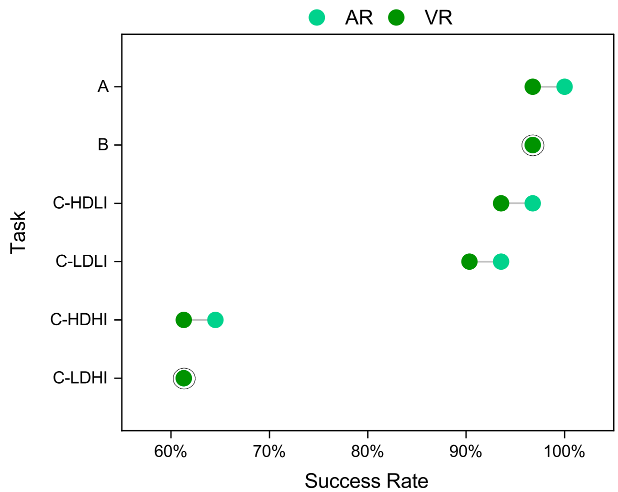


Figure 6.14: Comparison between success rates of AR and VR for the different tasks (horizontal scale restricted for increased visibility of the differences).

6.2.3 Influence of visual detail

In the scope of RQ3, we wanted to understand the impact of visual detail on data analysis performance. In particular, we wanted to know if using photographic textures in models influenced data analysis. For that purpose, we asked the participants to perform a set of tasks with the *DamXR* application where the 3D objects would alternately be presented with and without textures (flat-shaded). This variation in models' texture was tested across the distinct modes (PC, AR and VR) but also across the distinct levels of data indirection (data overlaid to the referent or in floating panels with charts).

To support the performance comparison between the two visual detail conditions across the distinct variations, a set of objective metrics were registered. In particular, we measured the time needed to complete each task and the task success (whether the participant gave the correct answer). Because for tasks TA and TB, visual detail did not change across different rounds of testing (and as such, we did not have *e.g.,* a non-textured counterpart), we restricted the analysis to the variants of task TC.

Concerning the completion times, we needed representative measures to compare the results of the two distinct visual detail cases (textured and non-textured). With that objective, we calculated, for each mode, two derived measures: the average completion times of tasks TC-HDLI and TC-HDHI and the average completion times of tasks TC-LDLI and

TC-LDHI. We named these derived measures, respectively, *AvgHD* (textured) and *AvgLD* (non-textured/flat-shaded).

For the PC mode, an *AvgHD* of 47.4 seconds (M = 44.2, SD = 18.7) was obtained, against a lower *AvgLD* of 41.5 seconds (M = 40.9, SD = 12.3). For the AR mode, the differences were in the opposite direction, with an *AvgHD* of 41.1 seconds (M = 34.6, SD = 29.1) and an *AvgLD* of 47.6 seconds (M = 47. SD = 17.2). The same tendency of lower completion times for variants using textures was registered for VR, with an *AvgHD* of 45.1 seconds (M = 38.9, SD = 34.0) against the 49.7 seconds (M = 45.6, SD = 31.0) of *AvgLD*. These differences are illustrated in Figure 6.15

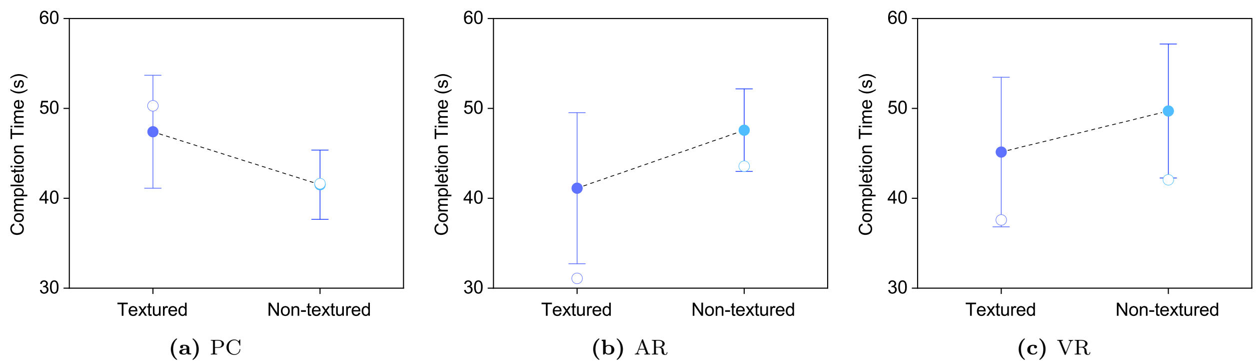


Figure 6.15: Average completion times for textured (*AvgHD*) and non-textured (*AvgLD*) variants for each of the modes (vertical scale restricted for increased visibility of the differences).

To understand the statistical significance of the variations of times between *AvgHD* and *AvgLD*, *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the completion times of variations of task TC that used textures (TC-HDLI and TC-HDHI) and the variations that did not use textures (TC-LDLI and TC-LDHI), for the AR, VR and PC modes. The results for each mode are presented in Table 6.8.

Task	W	Z	r	p	Sig.
PC	98.0 (+)	-2.939	-0.5279	0.003	✓
AR	147.0 (–)	-1.979	-0.3554	0.048	✓
VR	144.0 (–)	-2.038	-0.3660	0.042	✓

Table 6.8: *Wilcoxon Signed-Rank Tests* for differences between the average completion times for textured variants (*AvgHD*) and the average completion times of non-textured variants (*AvgLD*).

Concerning task success, we needed representative measures to compare the results of the two distinct visual detail cases (textured and non-textured). With that objective, we calculated, for each mode, two derived measures: the success percentage for the total number of tasks of the TC-HDLI and TC-HDHI variants and the success percentage for the total number of tasks of the TC-LDLI and TC-LDHI variants. We named these derived measures, respectively, *SPerHD* (textured) and *SPerLD* (non-textured/flat-shaded).

For the PC mode, equal results of *SPerHD* and *SPerLD* were obtained (82.3% ± 9.5%). For the AR mode the *SPerHD* result was 80.6% ± 9.8% and *SPerLD* was 77.4% ± 10.4%. The tendency of higher task success rates for variants using textures was also registered for VR, with 77.4% ± 10.4% against the 75.8% ± 10.7% of *SPerLD*. These differences are illustrated in Figure 6.16.

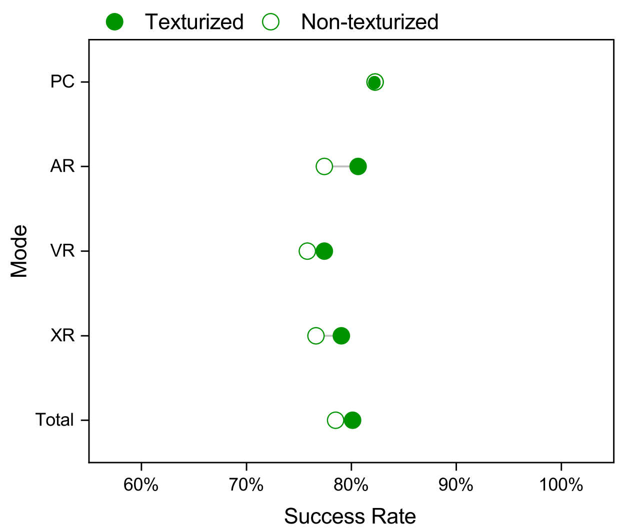


Figure 6.16: Comparison between task success rates for textured and non-textured variants, for each of the modes (PC, AR, VR), for the combination of XR modes, and for all the modes combined (horizontal scale restricted for increased visibility of the differences).

To assess the statistical significance of the differences between each task success results for the two distinct visual detail cases (textured and non-textured), *McNemar's Tests* were carried out. However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the task success results for the two visual detail cases.

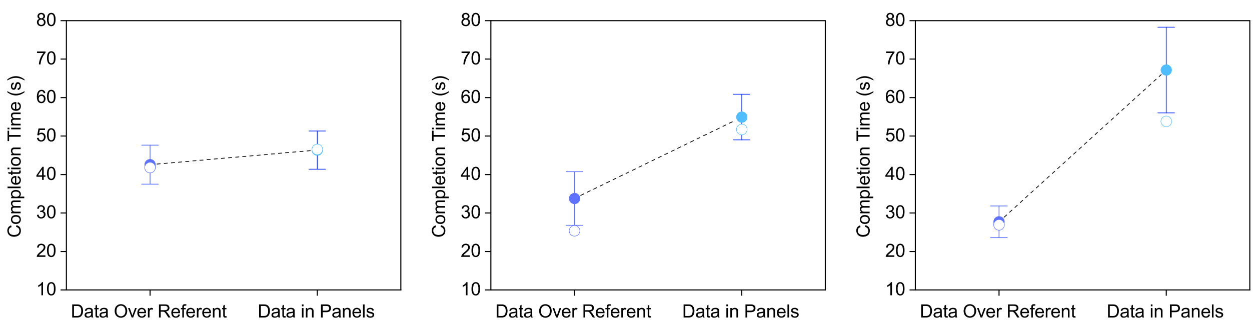
6.2.4 Influence of data indirection

In the scope of RQ4, we wanted to understand the impact of data indirection on analysis performance. In particular, we wanted to know if the use of distinct levels of data indirection had any influence on data analysis performance. For that purpose, we asked the participants to perform a set of tasks with the *DamXR* application where data would alternately be presented directly overlaid over the dam model or in charts located in floating panels. This variation in data indirection was tested across the distinct modes (PC, AR and VR) but also across the distinct levels of visual detail (textured and non-textured).

To support the performance comparison between the two visual detail conditions across the distinct variations, a set of objective metrics were registered. In particular, we measured the time needed to complete each task and the task success (whether the participant gave the correct answer). Because for tasks TA and TB, data indirection did not change across different rounds of testing (and as such, we did not have *e.g.,* representation of data in panels), again, we restricted the analysis to the variants of task TC.

Concerning the completion times, we needed representative measures to compare the results of the two distinct data indirection cases (data over the referent and data in panels). With that objective, we calculated, for each mode, two derived measures: the average completion times of tasks TC-HDLI and TC-LDLI and the average completion times of tasks TC-HDHI and TC-LDHI. We named these derived measures, respectively, *AvgLI* (data over referent) and *AvgHI* (data in panels).

For the PC mode, an *AvgLI* of 42,6 seconds (M = 40.3, SD = 15.5) was obtained, against a higher *AvgHI* of 46.4 seconds (M = 41.9, SD = 16.5). For the AR mode, the differences were in the same direction, with an *AvgLI* of 33.8 seconds (M = 27.9, SD = 24.1) and a higher *AvgHI* of 54.9 seconds (M = 50.1, SD = 18.9). The same tendency of lower completion times for variants using data represented over the referent was registered for VR, with an *AvgLI* of 27.7 seconds (M = 25.3, SD = 13.6) against the 67.2 seconds (M = 55.5, SD = 33.9) of *AvgHI*. These differences are illustrated in Figure 6.17.



(a) PC **(b)** AR **(c)** VR

Figure 6.17: Average completion times for data represented over the referent (*AvgLI*) and data represented in panels (*AvgHI*) variants for each of the modes (vertical scale restricted for increased visibility of the differences).

To understand the statistical significance of the variations of times between *AvgLI* and *AvgHI*, *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the completion times of variations of task TC that used data represented over the referent (TC-HDLI and TC-LDLI) and the variations where data was represented in panels (TC-HDHI and TC-LDHI), for all the modes. The results for each mode are presented in Table 6.9.

Task	W	Z	r	p	Sig.
PC	144.0 (−)	-2.038	-0.3660	0.042	✓
AR	22.0 (−)	-4.429	-0.7955	< 0.001	✓
VR	0.0 (−)	-4.860	-0.8729	< 0.001	✓

Table 6.9: *Wilcoxon Signed-Rank Tests* for differences between the average completion times for textured variants (*AvgHD*) and the average completion times of non-textured variants (*AvgLD*).

Concerning the task success, we needed representative measures to compare the results of the two distinct data indirection cases (data over the referent and data in panels). With that objective, we calculated, for each mode, two derived measures: the success percentage for the total number of tasks of the TC-HDLI and TC-LDLI variants and the success percentage for the total number of tasks of the TC-HDHI and TC-LDHI variants. We named these derived measures, respectively, *SPerLI* (data over the referent) and *SPerHI* (data in panels).

For the PC mode, a *SPerLI* of 72.6% ± 11.1% was obtained, against a higher *SPerHI* of 91.9% ± 6.8%. For the AR mode, the differences followed the opposite direction, with a *SPerLI* of 95.2% ± 5.3% and a *SPerHI* of 62.9% ± 12.0%. The tendency of higher task success rates for variants using data directly represented over the referent was also registered for VR, with 91.9% ± 6.8% against the 61.3% ± 12.1% of *SPerHI*. These differences are illustrated in Figure 6.18.

To assess the statistical significance of the differences between each task success results for the two distinct data indirection cases (data over the referent and data in panels), *McNemar's Tests* were carried out. The results of these tests are presented in Table 6.10.

Mode	N	OR	p	Sig.
PC	62	0.172	0.004	✓
AR	62	9.000	< 0.001	✓
VR	62	13.667	< 0.001	✓
XR	124	12.143	< 0.001	✓
Total	186	2.543	< 0.001	✓

Table 6.10: *McNemar's Tests* results for differences between each task success results for the two distinct data indirection cases (data over the referent and data in panels). The results encompass different modes (PC, AR, VR), the combination of XR modes, and all the modes combined.

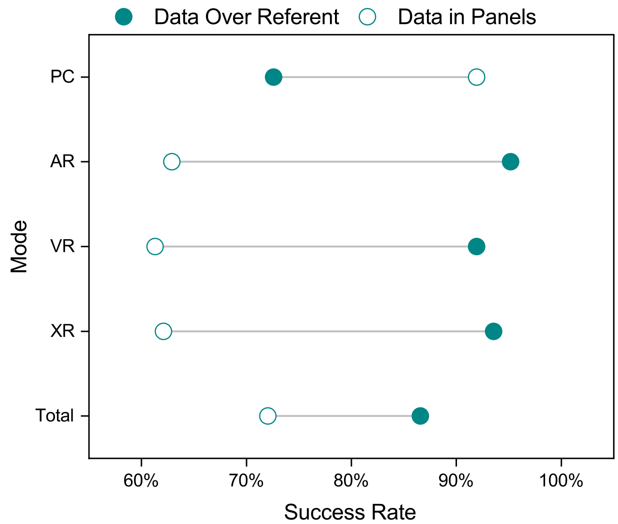


Figure 6.18: Comparison between task success rates for data indirection variants consisting of data over the referent and in panels, for each of the modes (PC, AR, VR), for the combination of XR modes, and for all the modes combined (horizontal scale restricted for increased visibility of the differences).

6.2.5 Combined effect of visual detail and data indirection

In the scope of RQ1-RQ4, we also carried out a wider-scope analysis with the objective of assessing how the interaction of the visual detail and data indirection factors would influence data analysis performance across modes and variants. Within that context, we compared the completion times and task success for tasks with and without textures, using data representation over the referent and on panels, using the different application modes.

We carried out *Friedman Tests* for each mode to assess the existence of significant differences in completion times across the four instances of visual detail and data indirection interaction (HDLI, LDLI, HDHI and LDHI). In addition, we computed *Kendall's Concordance Coefficient* (W_K) as a non-parametric effect size measure to quantify the strength of the observed differences [26]. We also performed post-hoc pairwise comparisons to identify how instances differed, using *Wilcoxon Signed-Rank Tests*, with *Bonferroni Correction*. Because for tasks TA and TB, visual detail and data indirection did not change across different rounds of testing, again, we restricted the analysis to the variants of task TC.

For AR and VR, the variants that achieved lower task completion times were the ones corresponding to lower spatial indirection and higher visual detail. In that scope, the variant with the lowest task completion time was HDLI, and the one with the highest task completion time was LDHI for both the XR modes. For the PC mode, the lower task completion times corresponded to the variants with lower visual detail. The lowest time was obtained with the LDLI variant, followed by LDHI (Figure 6.19).

Completion times for the PC mode exhibited statistically significant differences, with a

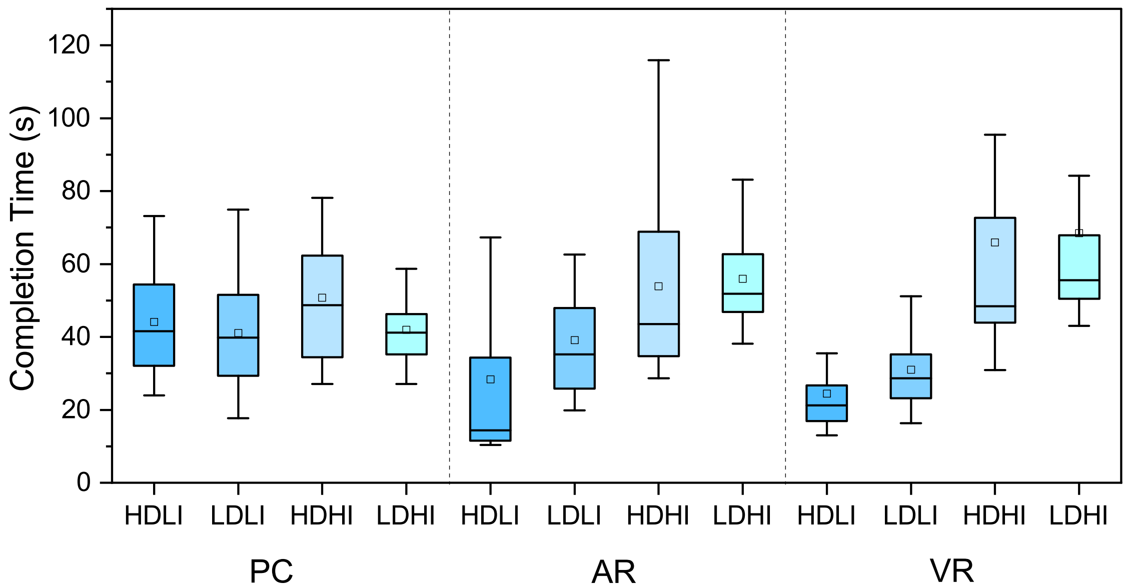


Figure 6.19: Completion times of the three modes (PC, AR, VR) across the four instances of visual detail and data indirection interaction (HDLI, LDLI, HDHI and LDHI).

chi-squared statistics of $\chi^2(3) = 12{,}871$, $p < 0.005$ (N = 31), $W_K = 0.138$ (small effect size). Statistically significant differences were also found for AR, with $\chi^2(3) = 47{,}245$, $p < 0.001$ (N = 31), $W_K = 0.508$ (large effect size) and VR, with $\chi^2(3) = 77{,}671$, $p < 0.001$ (N = 31), $W_K = 0.835$ (very large effect size). The results of the pairwise analysis carried out to identify which tasks contributed to the difference are presented in Table 6.11. For this pairwise analysis, a Bonferroni-corrected value of $\alpha = 0.05/4 = 0{,}0125$ was used.

In addition to the individual interaction of visual detail and data indirection for each mode, we wanted to assess the global effect of this interaction across modes. With that objective, we carried out a *Friedman Test* for the average completion times for each of the four variants. This procedure aimed to determine the existence of significant differences in global completion times across the four instances of visual detail and data indirection interaction (HDLI, LDLI, HDHI and LDHI). In addition, we once again computed *Kendall's Concordance Coefficient* (W_K) as a non-parametric effect size measure to quantify the strength of the observed differences. We also performed post-hoc pairwise comparisons to identify how variants differed, using *Wilcoxon Signed-Rank Tests*, with *Bonferroni Correction*. For similar reasons to those discussed in the previous analysis, we restricted this analysis to the variants of task TC.

From a global point of view, considering the average results, the variant corresponding to the lowest completion time was HDLI. The highest completion time was obtained with the LDHI variant (Figure 6.20).

The average completion times (PC, AR, VR) exhibited statistically significant differ-

Mode	Pair	W	Z	r	p	Sig.
PC	HDLI-LDLI	124.0 (+)	-2.430	-0.436	0.015	-
	HDLI-HDHI	135.0 (−)	-2.214	-0.398	0.027	-
	HDLI-LDHI	244.0 (+)	-0.078	-0.014	0.938	-
	LDLI-HDHI	88.0 (−)	-3.135	-0.563	0.002	✓
	LDLI-LDHI	164.0 (−)	-1.646	-0.296	0.100	-
	HDHI-LDHI	109.0 (+)	-2.724	-0.489	0.006	✓
AR	HDLI-LDLI	115.0 (−)	-2.606	-0.468	0.009	✓
	HDLI-HDHI	50.0 (−)	-3.880	-0.697	< 0.001	✓
	HDLI-LDHI	59.0 (−)	-3.704	-0.665	< 0.001	✓
	LDLI-HDHI	44.0 (−)	-3.998	-0.718	< 0.001	✓
	LDLI-LDHI	35.0 (−)	-4.174	-0.75	< 0.001	✓
	HDHI-LDHI	217.0 (−)	-0.607	-0.109	0.544	-
VR	HDLI-LDLI	63.0 (−)	-3.625	-0.651	< 0.001	✓
	HDLI-HDHI	0.0 (−)	-4.860	-0.873	< 0.001	✓
	HDLI-LDHI	0.0 (−)	-4.860	-0.873	< 0.001	✓
	LDLI-HDHI	1.0 (−)	-4.840	-0.869	< 0.001	✓
	LDLI-LDHI	0.0 (−)	-4.860	-0.873	< 0.001	✓
	HDHI-LDHI	183.0 (−)	-1.274	-0.229	0.203	-

Table 6.11: Post-hoc pairwise analysis of completion times across the four instances of visual detail and data indirection interaction, using *Wilcoxon Signed-Rank Tests*, with *Bonferroni Correction*.

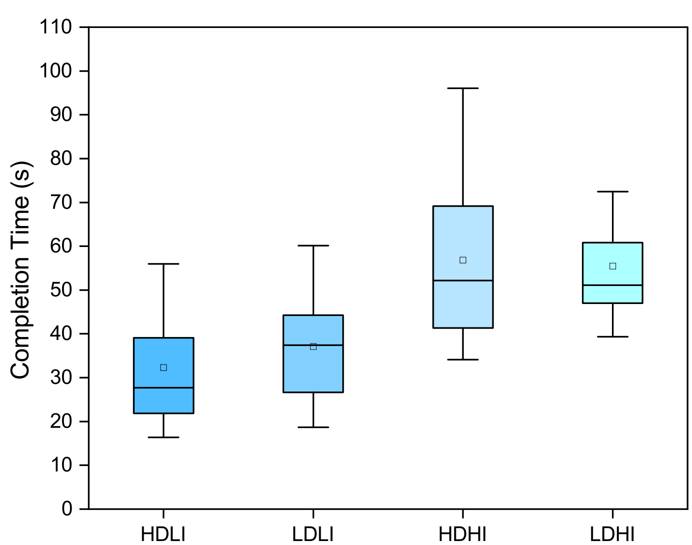


Figure 6.20: Completion times for the three modes (PC, AR, VR) across the four variants of visual detail and data indirection interaction (HDLI, LDLI, HDHI and LDHI).

ences among the four variants (HDLI, LDLI, HDHI and LDHI). A chi-squared statistics of $\chi^2(3) = 60.019$, $p < 0.001$ ($N = 31$), $W_K = 0.645$ (large effect size) was obtained. The results of the pairwise analysis carried out to identify which tasks contributed to the difference are presented in Table 6.12. For this pairwise analysis, a Bonferroni-corrected value of $\alpha \approx 0{,}0125$ was used.

Pair	W	Z	r	p	Sig.
HDLI-LDLI	129.0	-2.508	-0.45	0.012	✓
HDLI-HDHI	55.0	-4.840	-0.869	< 0.001	✓
HDLI-LDHI	21.0	-4.840	-0.869	< 0.001	✓
LDLI-HDHI	82.0	-4.801	-0.862	< 0.001	✓
LDLI-LDHI	41.0	-4.664	-0.838	< 0.001	✓
HDHI-LDHI	104.0	-0.157	-0.028	0.875	-

Table 6.12: Post-hoc pairwise analysis of the completion times across the four instances of visual detail and data indirection interaction, using *Wilcoxon Signed-Rank Tests*, with *Bonferroni Correction*.

We also carried out *Cochran's Q Tests* to assess the existence of significant differences in task success across the four instances of visual detail and data indirection interaction (HDLI, LDLI, HDHI and LDHI). In addition, *Generalized Eta-squared* (η^2) was computed to quantify the magnitude of the observed differences, providing a non-parametric effect size estimate for each test [27]. Furthermore, we performed post-hoc pairwise comparisons to identify how instances differed, using *McNemar's Tests*, with *Bonferroni Correction*. *Odds Ratios* (OR) were also calculated for each pair to estimate the direction and strength of performance shifts between conditions [116]. For pairs with zero discordant cases, the *Haldane–Anscombe Correction* [7], [62] was applied to obtain stable OR estimates. Because for tasks TA and TB, visual detail and data indirection did not change across different rounds of testing, we once more restricted the analysis to the variants of task TC.

For AR and VR, the variants that achieved higher task success were the ones corresponding to lower spatial indirection. In that scope, the variant with the highest task success was HDLI, and the one with the lowest task success was LDHI for both the XR modes. In Figure 6.21, we can see that for these modes, data indirection had a much higher impact than visual detail in task success. For the PC mode, the highest task success corresponded to the variants with lower visual detail and higher spatial indirection.

Task success for the PC mode exhibited statistically significant differences, with a $Q(3) = 9.250$, $p = 0.026$ ($N = 31$), $\eta^2 = 0.090$ (small effect size). Statistically significant differences were also found for AR, with $Q(3) = 19.548$, $p < 0.001$ ($N = 31$), $\eta^2 = 0.174$ (large effect size) and VR, with $Q(3) = 19.105$, $p < 0.001$ ($N = 31$), $\eta^2 = 0.170$ (large effect size). The results

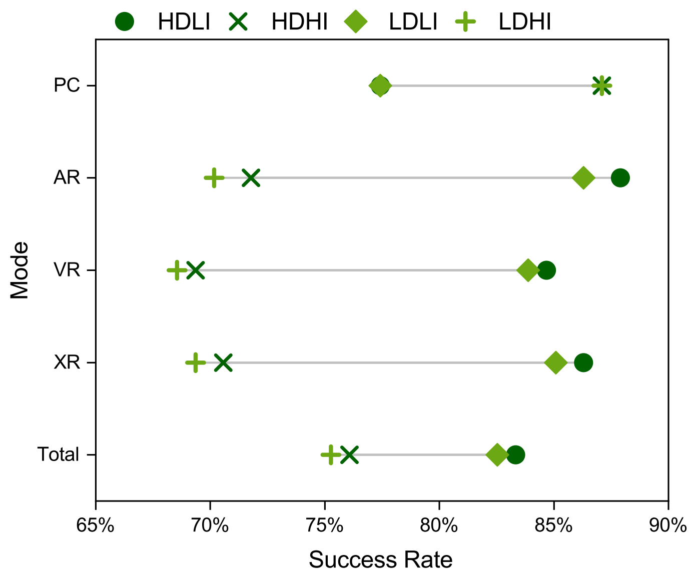


Figure 6.21: Comparison between task success rates across for the four instances of visual detail and data indirection interaction for each of the modes (PC, AR, VR), for the combination of XR modes, and for all the modes combined (horizontal scale restricted for increased visibility of the differences).

of the pairwise analysis carried out to identify which tasks contributed to the difference are presented in Table 6.13. For this pairwise analysis, a Bonferroni-corrected value of $\alpha = 0.05/4 \approx 0{,}0125$ was used.

In addition to the individual interaction of visual detail and data indirection for each mode, we wanted to assess the global effect of this interaction across modes. With that objective, we carried out a *Cochran's Q Test* for the accumulated task success for each of the four instances (considering the aggregation of the three modes for each instance). This procedure aimed to determine the existence of significant differences in task success across the four instances of visual detail and data indirection interaction (HDLI, LDLI, HDHI and LDHI). *Generalized Eta-squared* (η^2) was once again computed to quantify the magnitude of the observed differences, providing. We also performed post-hoc pairwise comparisons to identify how instances differed, using *McNemar's Tests*, with *Bonferroni Correction*. *Odds Ratios* (OR) with *Haldane–Anscombe Correction* were also calculated for each pair to estimate the direction and strength of performance shifts between conditions. For similar reasons to those discussed in the previous analysis, we restricted this analysis to the variants of task TC.

The aggregation of task success results (PC + AR + VR) exhibited statistically significant differences among the four variants (HDLI, LDLI, HDHI and LDHI). A $Q(3) = 13.419$, $p = 0.004$ ($N = 93$), $\eta^2 = 0.046$ (small effect size) was obtained. The results of the pairwise analysis carried out to identify which tasks contributed to the difference are presented in

Mode	Pair	N	*OR*	*p*	Sig.
PC	HDLI-LDLI	31	1.154	1.000	-
	HDLI-HDHI	31	0.231	0.125	-
	HDLI-LDHI	31	0.077	0.031	-
	LDLI-HDHI	31	0.294	0.109	-
	LDLI-LDHI	31	0.176	0.039	-
	HDHI-LDHI	31	0.600	1.000	-
AR	HDLI-LDLI	31	1.667	1.000	-
	HDLI-HDHI	31	7.667	0.006	✓
	HDLI-LDHI	31	23.000	< 0.001	✓
	LDLI-HDHI	31	19.000	0.004	✓
	LDLI-LDHI	31	7.667	0.006	✓
	HDHI-LDHI	31	1.133	1.000	-
VR	HDLI-LDLI	31	3.000	1.000	-
	HDLI-HDHI	31	21.000	0.002	✓
	HDLI-LDHI	31	7.667	0.006	✓
	LDLI-HDHI	31	7.000	0.012	✓
	LDLI-LDHI	31	7.000	0.012	✓
	HDHI-LDHI	31	1.000	1.000	-

Table 6.13: Post-hoc pairwise analysis of task success across the four instances of visual detail and data indirection interaction, using *McNemar's Tests*, with *Bonferroni Correction*.

Table 6.14. For this pairwise analysis, a Bonferroni-corrected value of $\alpha \approx 0{,}0125$ was used.

Pair	*N*	*OR*	*p*	Sig.
HDLI-LDLI	93	1.400	0.629	-
HDLI-HDHI	93	3.000	0.009	✓
HDLI-LDHI	93	3.000	0.009	✓
LDLI-HDHI	93	2.263	0.045	-
LDLI-LDHI	93	2.143	0.052	-
HDHI-LDHI	93	1.000	1.000	-

Table 6.14: Post-hoc pairwise analysis of the accumulated task success (PC & AR & VR) across the four instances of visual detail and data indirection interaction, using *McNemar's Tests*, with *Bonferroni Correction*.

6.2.6 Multivariate effects of reality modality, visual detail, and data indirection

Within the scope of RQ2–RQ4, we wanted to complement the previous analyses by further examining how visual detail and data indirection affected user performance specifically within the immersive modes. To address task completion times, we conducted a multi-factorial repeated measures *ANOVA* [106], focusing exclusively on immersive modes. The goal was to identify the joint and interaction effects of the three within-subjects factors: reality modality (AR, VR), visual detail (HD, LD), and data indirection (LI, HI) (Figure 6.22).

The analysis was conducted using the *General Linear Model* [114], [128] procedure with the previously mentioned within-subjects factors. The model was specified using a full factorial design (modality × detail × indirection), and Type III sum of squares was used. *Bonferroni*-corrected pairwise comparisons were employed, and effect sizes were estimated using Partial Eta-Squared (η_p^2). *Mauchly's Test of Sphericity* [107] confirmed that sphericity was not violated (W = 1.000), so no correction was needed for degrees of freedom.

The multivariate test results show that the main effect of reality modality was not statistically significant (Wilks' $\Lambda = 0.979$, $F(1, 30) = 0.655$, $p = .425$, $\eta_p^2 = .021$). In contrast, visual detail showed a strong, statistically significant main effect (Wilks' $\Lambda = 0.164$, $F(1, 30) = 152.71$, $p < .001$, $\eta_p^2 = .836$). Similarly, indirection also had a significant main effect (Wilks' $\Lambda = 0.747$, $F(1, 30) = 10.18$, $p = .003$, $\eta_p^2 = .253$).

In what concerns interaction effects, the results suggest that the effect of visual detail differs across the two distinct reality modalities. Specifically, the penalty of using low visual detail was greater in VR. In this context, the interaction effect of immersive mode × detail is statistically significant ($F(1, 30) = 13.06,\ p = 0.001,\ \eta^2 = 0.303$). However, the interaction effects of mode × indirection and detail × indirection, as well as the three-way interaction of mode × detail × indirection, were not significant.

Regarding pairwise comparisons, the results show a strong and statistically significant effect of visual detail on task completion time, across conditions, with a mean difference $MD = -30.31\,\mathrm{s}$, $p = .001$, $\eta_p^2 = .836$ (very large effect). This finding indicates that higher-detail representations consistently led to faster task performance in both modes.

Concerning data indirection, tasks involving low indirection were also completed significantly faster than those with high indirection, with $MD = -5.52\,\mathrm{s}$, $p = .003$, and $\eta_p^2 = .253$ (moderate effect). In contrast, the difference between immersive modes was not statistically significant, indicating minimal influence of AR versus VR on performance when other factors are controlled.

To examine the effects of reality modality, visual detail, and data indirection on task

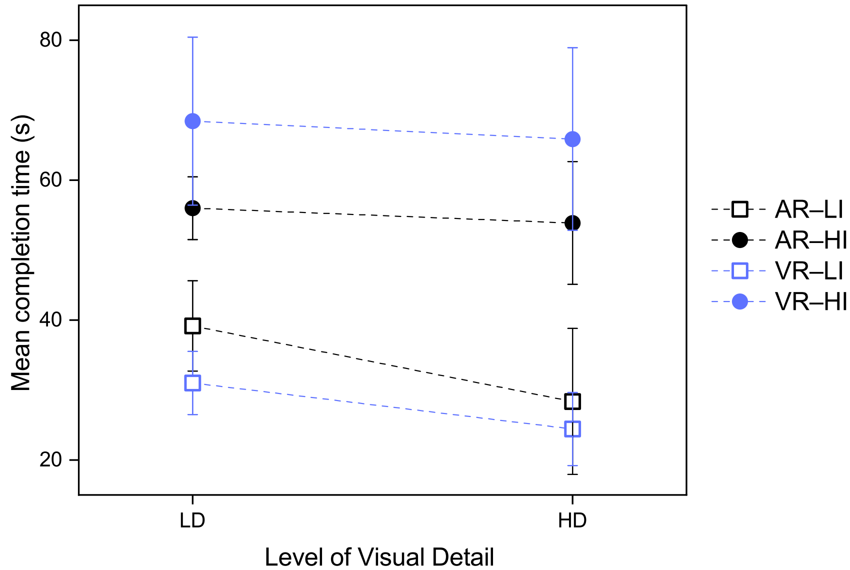


Figure 6.22: Task completion time for AR vs VR across visual-detail (LD/HD) and data representation indirection levels (LI/HI) (vertical scale restricted for increased visibility of the differences).

success (Figure 6.23), a *Generalized Estimating Equations* [86] approach was employed (31 participants, eight trials each, with 248 observations in total). The model assumed a binomial distribution with a logit link function [30]. An exchangeable working correlation structure was specified to account for within-subject correlations across eight observations per participant. The model included all main effects, as well as their two-way and three-way interactions. Parameter estimation was conducted using the *Fisher Scoring* method [53], and hypothesis testing for each effect was performed using *Type III Wald Chi-square* tests [168]. To evaluate model fit, the *Quasi-likelihood under the Independence Model Criterion* (QIC) was used [122].

Model fit was acceptable, with a QIC of 238.68. The results indicate that the level of indirection exerted a notable influence on performance ($\chi^2(1) = 16.09,\ p < .001$), whereas neither the immersive mode nor the level of visual detail reached statistical significance. All two and three-way interactions were likewise non-significant. In that scope, parameter estimation showed that moving from low to high indirection increased the log-odds of failure by 1.774[9] (SE = 0.649), which corresponds to an odds ratio of 5.89 with a 95% confidence interval from 1.65 to 21.0.

To that extent, a participant carrying out a task with low indirection conditions had an estimated 93% chance of success. However, this likelihood fell to 63% when the same task was performed under high indirection. By contrast, neither AR relative to VR nor high relative to low visual detail, alone or in combination, altered the outcome.

[9]Failure was the reference, so this coefficient is positive

Thus, we can infer that success depends heavily on data representation indirection. High indirection consistently hurts performance, no matter whether the mode is AR or VR or whether high or low visual detail is used.

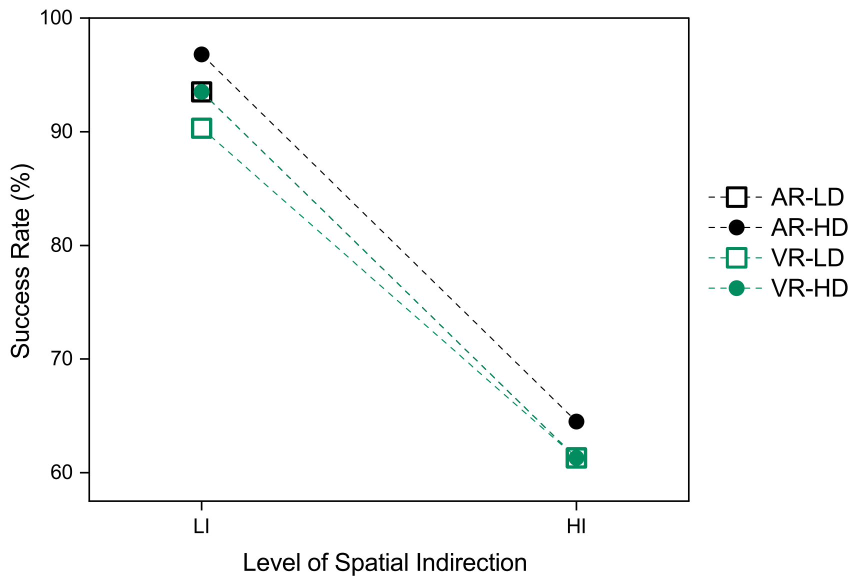


Figure 6.23: Success rate for AR vs VR across data representation indirection (LI/HI) and visual-detail (LD/HD) levels (vertical scale restricted for increased visibility of the differences).

6.2.7 Influence of participant demographics and background

We also wanted to explore how the sociodemographic characteristics of participants related to the study outcomes. Specifically, we aimed to investigate whether and how factors such as age, gender, educational level, or prior experience with XR technologies affected the user experience and analysis performance measured metrics.

To identify potential relationships between participants' background characteristics and their performance in each experimental condition, we conducted an exploratory[10] correlation analysis. Because preliminary inspection (*Shapiro–Wilk Tests* and Q-Q plots) showed that most distributions were markedly non-normal and some variables were binary, *Spearman* [58] rank–order correlation coefficients (ρ) were computed for all variable pairs.

Sociodemographic predictors, including age, gender, education level, years of professional experience, familiarity with XR, were entered alongside performance (completion time and

[10] The presented results are nominal (unadjusted) as this exploratory screen was solely intended to highlight potential patterns. Adjusted p-values (using *e.g.,* the *Benjamini–Hochberg* [13] procedure) were not calculated due to the localized nature of the effects, but would be necessary to contextualize the robustness against multiple testing.

success) and user experience (SUS and user experience attributes scores) outcome measures for the multiple reality modalities, level of detail and data indirection.

Regarding objective metrics, task-completion time was mostly insensitive to demographics, with some localized exceptions. A specific example of those exceptions was the impact of age on task time for the AR and PC modes for certain variants. Indeed, older participants were slower in Task B using the PC mode ($\rho = .42$, $p = .020$) and in Task A ($\rho = .38$, $p = .0036$) and the LDLI variant of Task C ($\rho = .55$, $p = .0001$) using the AR mode. Another example was the positive influence of a higher education level on task speed. That influence was only observed with the LDLI variant of Task C when using the AR mode ($\rho = -.38$, $p = .037$). Nevertheless, the same tendencies were not verified, with nominal significance, for other task complexity levels, variants, and reality modality.

Likewise, success rate was generally not significantly influenced by demographics, apart from localized exceptions. Such exceptions include the positive influence on success of a higher education for the LDLI variant of Task C, using the VR mode ($\rho = .39$, $p = .048$). Familiarity with XR also influenced success rate positively, but only for the HDHI variant of Task C, using the VR mode ($\rho = .40$, $p = .026$)

Concerning the subjective metrics measured, we found no significant association between age and experience in dam-safety control activities and user experience scores. Prior familiarity with XR technology also did not translate into higher user experience scores.

We did, however, find localized effects concerning gender and education level. Female participants, *e.g.,* found the AR mode to be more immersive than males ($\rho = -.37$, $p = .043$). In contrast, males found the experience provided by the PC mode to be more memorable (higher post-use impact) than females ($\rho = .36$, $p = .046$). Likewise, less academically qualified participants found the PC mode to correspond to a higher post-use impact than more educated participants ($\rho = -.46$, $p = .009$).

Overall, and except for the localized pockets previously mentioned, we found that performance and user experience were largely agnostic to demographics and that, as such, modality-specific design variants had a much more substantial impact than the participants' profiles. Hence, the demographic composition is unlikely to have biased significantly the main results.

6.2.8 Perception of usefulness and practicability

Regarding the assessment of the participant's changes in perception of the usefulness and practicability of XR technologies, before and after experimenting with the *DamXR* application, we obtained the results illustrated in Figure 6.24. To understand the statistical significance of the variations of scores given by participants, *Wilcoxon Signed-Rank Tests* were carried out, with prior assessments of the distribution nonnormality (using *Shapiro–Wilk Tests*).

Regarding the usefulness of XR in the dam safety control activity, participants' perception increased for both VR and AR. Indeed, in what concerns VR usefulness perception, the average scores given by participants (Table B.1, question #1) increased from 3.6 (M = 4.0, SD = 1.1) to 4.0 (M = 4.0, SD = 0.9), indicating that the user's opinion on the usefulness was more favorable after using the prototype. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of scores, with $p < 0.008$ (W = 4.0, Z = -2.667, r = -0.4790).

Concerning AR usefulness perception, the average scores given by participants (Table B.1, question #2) increased from 3.6 (M = 3.0, SD = 0.9) to 3.9 (M = 4.0, SD = 1.1), indicating that the user's opinion on the usefulness was more favorable after using the prototype. The results offer evidence against the supposition of no statistically significant difference between the two sets of scores, with $p < 0.045$ (W = 26.0, Z = -2.000, r = -0.3592).

The perception of the practicability of XR headsets in the context of dam safety control (Table B.1, question #3) was also measured. The average scores given by participants increased from 2.9 (M = 3.0, SD = 1.1) to 3.3 (M = 3.0, SD = 1.3), indicating that the participants perceived XR headsets as more practical after using the prototype. However, the results do not provide sufficient evidence to reject the null hypothesis, indicating no statistically significant difference between the two sets of scores.

The participants were also questioned about their opinion regarding the spatial perception of 3D in XR environments when compared with a desktop computer screen. The average scores given by participants (Table B.1, question #4) increased from 3.5 (M = 4.0, SD = 1.3) to 4.0 (M = 4.0, SD = 1.1), indicating that the user's opinion on the advantages of 3D data spatial perception was more positive after using the prototype. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of scores, with $p < 0.037$ (W = 45.0, Z = -2.086, r = -0.3747).

We also inquired the participants about their opinion regarding the visualization of data directly overlaid over the representation of the physical referent compared to the visualization of data in traditional charts. The average scores given by participants (Table B.1, question #5) went from 3.8 (M = 4.0, SD = 1.0) to 4.3 (M = 5.0, SD = 0.9), indicating that they increased their positive opinion on the advantages of overlaying data directly over the dam model. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of scores, with $p < 0.025$ (W = 36.5, Z = -2.235, r = -0.4014).

The perceived advantages for data analysis in the use of referent models with realistic textures (Table B.1, question #6) were also assessed among the participants. The average scores given by participants increased from 3.5 (M = 4.0, SD = 0.9) to 3.9 (M = 4.0, SD = 0.8), indicating that they had a more positive opinion on the use of models with realistic textures after using the prototype. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of scores, with $p < 0.040$ (W = 54.0, Z = -2.057, r = -0.3694).

Finally, the opinion variation of participants regarding the advantages of including terrain and other surrounding elements in the physical referent representation was addressed (Table B.1, question #7). The average scores given by participants went from 3.2 (M = 4.0, SD = 1.3) to 3.7 (M = 4.0, SD = 1.2), indicating that they increased their positive opinion on the use of additional elements to the referent model. The results offer evidence rejecting the null hypothesis, indicating a statistically significant difference between the two sets of scores, with $p < 0.047$ (W = 31.0, Z = -1.989, r = -0.3572).

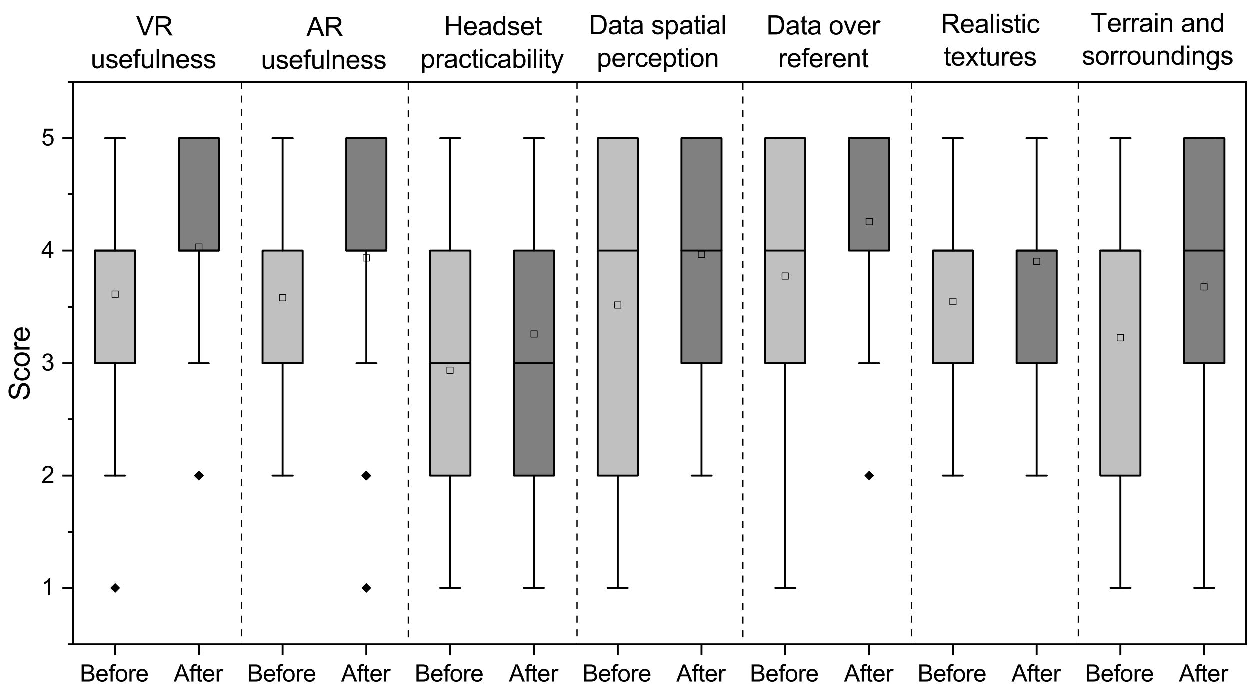


Figure 6.24: Participants' change in perception regarding the usefulness and practicability of distinct aspects of XR technology, models' visual fidelity, and data representation type. For each aspect, the scores obtained before the participants interacted with the prototype and after they finished the proposed tasks at the end of the test session are depicted.

6.3 Discussion

As we mentioned at the beginning of the chapter, this user study aimed to understand if immersive environments could offer tangible advantages in dam safety control data analysis tasks. Within this wider objective, we wanted to address the specific aspects corresponding to the research questions RQ1-RQ4. These aspects will be covered in the following sections.

6.3.1 RQ1: XR vs. PC

The first of the objectives was determining if there existed performance and/or user-experience advantages in using *off-site* XR in dam data visualization (immersive *proxsituated* environments) over conventional 2D desktop visualization (RQ1). We wanted to know if aspects like the added immersion or increased engagement brought by XR, addressed in Sections 2.1 and 2.2 and exemplified in Sections 3.1 and 3.2 would have a positive outcome in the physical referent contextualization processes discussed in Section 2.3 and exemplified in Sections 3.3 and 3.4.

In Section 6.2.1, we first started by presenting the results of a SUS questionnaire filled out by participants. These results indicate a significant preference for the XR modes as a whole compared to the PC mode. The general preference for XR was circumscribed to particular aspects using the subsequent user experience questionnaire. Three of these aspects can be pinpointed as the ones most significantly contributing to the XR advantage: immersiveness, engagement, and satisfaction.

However, there are also aspects where the PC seemed to offer advantages over some of the XR modes. These aspects include the perceived effort and comfort, where PC had a significant advantage over VR. Such an advantage in terms of comfort might be directly related to the type of device used for the XR modes. Indeed, while XR headsets have evolved with regard to some of their characteristics, like field of view and refresh rate [140], over the years, discomfort will still exist in specific settings or with specific individuals (*e.g.,* motion sickness or disorientation resulting from full immersion in virtual worlds). Moreover, the disadvantage in perceived effort might related to the participants' lack of experience with XR technologies. Nonetheless, further research would be needed to determine the exact reason for the disadvantages shown by XR in these two aspects.

AR and VR also seem to have, individually, significant advantages over PC. An example is data clarity where XR as a whole did not have substantial advantages, but AR individually showed significantly better results than PC.

The existence of analysis performance differences between XR and PC was also examined through the registration of objective metrics during the execution of tasks by participants.

Concerning the time to complete each task, XR achieved lower completion times in four of the tasks (TA, TB, TC-HDLI and TC-LDLI) and significantly lower completion times for the two of those tasks with higher complexity (TC-HDLI and TC-LDLI). However, PC had significantly lower completion times for the other two remaining higher complexity tasks (TC-HDHI and TC-LDHI). The lowest overall task completion time was achieved by XR. So, indeed, in certain conditions, XR seems to have a significant advantage over PC in what concerns task completion speed.

With regards to task success, AR had a significantly higher success than PC for three of the tasks (TB, TC-HDLI, TC-LDLI). At the same time, the inverse happened for two of the tasks (TC-HDHI, TC-LDHI), as depicted in Figure 6.10 (a) and Table 6.6. VR had a significantly higher task success than PC for two tasks (TB, TC-HDLI), and the opposite was registered for the other two higher complexity tasks (TC-HDHI, TC-LDHI), as depicted in Figure 6.10 (b) and Table 6.6. The highest success rates were achieved by both AR and VR when compared to PC. As such, in certain conditions, XR seems to have a significant advantage over PC regarding task success.

Therefore, from our findings, we can infer that **concerning RQ1, XR has significant advantages in some aspects of user experience over PC** (immersiveness, engagement, and satisfaction). However, the PC was more comfortable and corresponded to a lower perceived effort.

Still **concerning RQ1, XR had significant advantages for some aspects of analytics performance and certain variants over PC**. Indeed, XR had significantly better completion times than PC for variants TC-HDLI and TC-LDLI, but was worse in other variants (TC-HDHI and TC-LDHI). Likewise XR had significantly higher task success than PC for certain variants (TB, TC-HDLI, TC-LDLI in AR and TB, TC-HDLI in VR), but lower for other variants (TC-HDHI, TC-LDHI when compared with AR and TC-HDHI, TC-LDHI when compared with VR).

6.3.2 RQ2: AR vs. VR

The second relevant objective of the user study was to assess whether there were relevant performance or user-experience differences in using *off-site* AR in *proxsituated* dam data visualization over VR (RQ2). As discussed in Sections 2.1, 2.2, and 2.3, the higher immersion brought by VR has the potential of improving aspects like presence and promoting engagement, but also sensorially encapsulates users, isolating them from the real world. AR offers a trade-off by allowing users to keep peripheral awareness of their surroundings, as exemplified in Sections 3.3 and 3.4. We aimed to compare how the virtues of each modality translate into structural data analysis performance and user experience.

In Section 6.2.2, we first started by presenting the results of a SUS questionnaire filled out by participants. While the results of this broader scope questionnaire are not conclusive, with the SUS scores on both realities being very near, some relevant differences in specific aspects between AR and VR were found when we carried out the more specific user experience questionnaire.

In the participant's opinion, VR had significant advantages over AR concerning immersiveness and engagement. However, AR was considered to correspond to a lower perceived effort than VR. AR was also significantly better regarding data clarity and more comfortable to use than VR.

These results seem to indicate that higher immersiveness modes, while more engaging, correspond to higher perceived effort and lower comfort. This tendency is on par with what was registered in the PC (lower immersiveness) - XR (higher immersiveness) comparison addressed in the previous section.

No significant differences were found between AR and VR in what concerns the other subjective metrics aspects addressed in the study (satisfaction, intuitiveness, user focus, feedback, and post-use-impact).

Concerning task completion times, AR corresponded to a slightly non-significant, overall shorter average completion time across all tasks. Moreover, regarding individual tasks, significant differences were only achieved for tasks in TC-LDLI, with an advantage for AR, which was faster than VR.

With regards to task success, AR, while having slightly more success in most tasks, did not significantly differ from the task success registered for VR.

Therefore, from our findings, we can deduce that **concerning RQ2, AR had significant differences in some aspects of user experience when compared with VR** (VR was better in immersiveness, engagement, and satisfaction and AR was better in perceived effort (lower), data clarity, and comfort).

Still **concerning RQ2, AR had no significant differences in analytics performance when compared with VR, with the exception of task completion times for one of the variants** (TC-LDLI where AR was better than VR).

6.3.3 RQ3: Textured vs. non-textured

The third specific objective of this study was to determine if visual fidelity within the XR *proxsituated* experience would impact the analysis performance (RQ3). We addressed a particular aspect of visual fidelity - the existence (higher fidelity) or absence (lower fidelity) of photographic textures in virtual environmental objects. We aimed to determine whether using higher visual detail would enhance contextualization by reinforcing the realism of the data referent, as discussed in Sections 2.3 and 3.4. Alternatively, the deliberate reduction in visual clutter, brought by flat shaded surfaces, could possibly facilitate data visualization and analysis.

Concerning the task completion times, there were significant differences between the textured and non-textured variants for all three modes (PC, AR and, VR). There was also a noticeable difference between how the textured and non-textured compared between PC and the XR modes. While on PC, participants had lower completion times using non-textured variants, for both AR and VR, the opposite was registered, with the textured variants achieving lower completion times than the non-textured.

Regarding task success, the results for both PC and the XR modes were very similar, with no significant differences registered for any of the modes.

Based on our findings, we can ascertain that **the answer to RQ3 is positive**. Visual detail has indeed a significant impact on analysis performance. For both AR and VR, the use of textures offers noticeable advantages, resulting in shorter completion times than the use of flat-shaded objects within the XR environment. Additionally, we found that the opposite happens when using PC, with non-textured/flat-shaded objects having performance advantages over the use of textures. However, our findings also indicate that visual detail (in particular, the use of textures) has no significant impact on task success rate.

6.3.4 RQ4: Lower vs. higher spatial indirection in data representation

Our fourth objective in conducting this study was to assess the impact of data spatial representation indirection (RQ4) on analysis performance. As we have seen in Section 2.3 and exemplified in Section 3.4, spatial indirection is one of the cornerstones of *proxsituated* visualization theory and an aspect that we believe could greatly influence how well data could be analyzed in the scope of dam structures representations. We addressed two specific configurations with distinct levels of spatial indirection: data represented directly over the referent (lower spatial indirection) and data represented in floating panels around the user (higher spatial indirection).

In regards to task completion times, the variants with lower spatial indirection data representation achieved significantly lower completion times across all modes (PC, AR and VR). We also observed that the differences between the two levels of spatial indirection were higher in modes corresponding to higher immersiveness. Indeed, the differences between the two sets of variants (lower and higher indirection) increase from PC to AR and from AR to VR, as seen in Figure 6.17.

Significant differences could also be found in task success between the two distinct data indirection levels. A higher task success was observed for lower data indirection (data over referent) for both AR and VR (and consequently also XR). The opposite result was recorded for PC, where the highest success rate corresponded to the higher data indirection variants (data in panels).

A substantially wider difference could also be found between the two data indirection levels on XR modes than on the PC mode. From this divergence in the magnitude of differences, we can infer that the impact (positive or negative) of the data indirection level on task success rates is higher on AR and VR than on PC.

Thus, our results indicate that **the answer to RQ4 is positive**. Spatial data representation indirection has a significant impact on the data analysis performance. However, the way it impacts the addressed modes differs. For AR and VR, a lower data indirection positively impacts performance, resulting in lower completion times and higher task success rates. For the PC/baseline mode, lower data indirection can positively or negatively impact analysis performance, depending on the metric considered. Lower data indirection results in faster completion times. However, it also results in lower task success rates.

6.3.5 RQ3 & RQ4: Additional assessments of visual detail and data indirection

We initially carried out analyses in a partitioned manner, considering one effect at a time. However, we also wanted to assess (in the scope of RQ3 and RQ4) the combined effect of the distinct variations of visual detail and data spatial representation indirection. As such, we analyzed the four proposed variants (HDLI, LDLI, HDHI and LDHI) for each mode (AR, VR and PC) and globally across all modes.

For the PC mode, the lowest task completion times were obtained for the LDLI variant (no textures and data over referent). However, LDLI was followed very closely by the variant at the opposite end of the data indirection spectrum, LDHI (no textures and data in panels).

For both AR and VR, the most performant variant in regards to task completion times was HDLI (textures and data over referent) at a significant distance from all the other variants. It was followed by LDLI, HDHI, and LDHI, in a downward order in terms of performance. Such a result seems to indicate that within the addressed variants, XR has better performance when using lower data indirection and higher visual detail.

For the XR modes, significant differences could also be found in task success between the several variations resulting from the combined effect of the distinct variations of visual detail and data spatial representation indirection. For both AR and VR, the variant HDLI achieved the highest task success rate at significant distances from the higher indirection variants (HDHI, LDHI). It was followed by the LDLI variant, which also had significant differences when compared to HDHI and LDHI.

In a more global analysis, considering each of the four variants for the set of all modes, HDLI (textures and data over referent) was again the variant with the highest performance in terms of task completion time. It was followed closely by LDLI (no textures and data over referent). The lowest performant variants for this metric were HDHI and LDHI, at a significant distance from the variants using lower data indirection. These results confirm a more significant contribution of data representation indirection over visual detail in the increase of data analysis performance.

Therefore, these results appear to further support **a positive answer to both RQ3 and RQ4**. The combined influence of visual detail and spatial data representation indirection significantly impacts the data analysis performance. This impact occurs for both addressed metrics (task completion time and success). However, the impact is noticeable in different ways depending on the use of XR or PC.

6.3.6 RQ2-RQ4: Multivariate assessment

We also carried out a multivariate analysis targeting the immersive modes with the objective of clarifying how our three design levers (reality modality (AR vs VR), visual detail, and spatial indirection) combined to shape performance.

The use of high levels of visual detail resulted in significant improvements in task speed, especially when higher immersion was used (VR mode), further supporting the importance of realistic texturing of the referent as a primary anchor for analysis performance. This result is in line with the insights detailed in Section 6.2.5, with higher visual detail variants corresponding to lower task completion times. Task success, however, was not significantly influenced by visual detail.

A higher data spatial indirection penalized both speed and success when using XR. Unlike visual detail, this penalty was mostly modality-agnostic as users performed worse regardless of being in AR or VR. This tendency supports the results discussed Section 6.2.5, with lower spatial indirection variants corresponding to both lower task completion times and higher task success. Such a tendency seems to support that multiplying referential hops (shifting between model and panel) indeed taxes analysis performance.

The analysis also confirmed that reality modality is secondary in terms of performance, when compared to the importance of other variables. However, it relevantly modulates the cost of low visual detail. Indeed, while AR and VR did not differ overall in speed or success, VR was disproportionately harmed by low visual detail.

As such, these results further support **a positive answer to both RQ3 and RQ4**. They also further substantiate that **concerning RQ2, AR has no significant differences in analytics performance when compared with VR**.

6.3.7 User sociodemographics

The exploratory correlation analysis described in Section 6.2.7 indicates that, once interface parameters are defined, sociodemographic participant characteristics exert markedly less influence on outcomes than modality, visual detail, or data indirection. Indeed, task completion time, task success, and user experience scores were mostly insensitive to demographics, with some localized exceptions.

Nevertheless, local pockets of sensitivity emerged that are worth mentioning: older participants were slower on some AR and PC variants, higher education and XR familiarity favored task success in specific cases, and gender tilted perception (of immersiveness and post-use impact), but not performance, in particular variants.

6.3.8 User perception on AR and VR

We also found it relevant to assess the impact that our user study could have had on the participant's perception of the usefulness and practicability of XR situated analysis environments in dam safety control. With that objective, the participants were asked a set of questions regarding such perception before and after having carried out the tasks.

The perceived usefulness of both AR and VR in dam safety control had a significant increase between the beginning and the end of the tests. Likewise, participants' opinions on the advantages of XR for improving the spatial perception of 3D data, in comparison with a PC, increased significantly. Such perception changes might be paired with the increased performance that participants experienced when carrying out tasks using some of the variants of the XR modes.

The participants' positive perception of the advantage of visualizing data overlaid on digital 3D models of dams, over representing that data in conventional charts also increased significantly. They also had a more favorable opinion on the upsides of using digital models of dams with realistic textures for dam data analysis. Such variation in perception may possibly be coupled with the better results in task completion time and task success for variants with lower data indirection and higher visual detail when compared with other variants.

Furthermore, the participants had an improved opinion on the benefits of representing the terrain and other elements surrounding dams in models used for data analysis. Such improvement in participants' opinion might be associated with the increased immersiveness and engagement registered in the VR mode when compared to AR and PC. Indeed, in the VR mode, both the dam structure, terrain, water bodies, and sky were represented for a better sense of presence.

In summary, the participants increased perception of the relevance of XR technologies for the dam safety control activity appears to indicate a positive impact of the *DamXR* application on the participants' opinion.

6.4 Limitations

When interpreting the results and outcomes of this user study, one should be aware of some of its limitations. The first limitation is the relatively small sample size. This limitation resulted from the need to use participants with very specific characteristics. Indeed, we wanted to understand the impact of XR situated methods in a real physical setting with actual domain experts. Using generic participants in generic physical settings would not have provided the same level of insight or validity for our use case. Due to the specificity of such activity, recruiting participants who were available to spare time from their already busy schedules to participate in user studies was not straightforward.

While the lower-difficulty tasks could have been carried out by non-expert users without a very thorough framing of the domain, other tasks implied a certain level of technical and analytical dexterity in the field (an assumption that can be inferred from the lower success rates on tasks with a higher level of difficulty). Such dexterity would unlikely be found among non-expert users. While we could have lowered the difficulty of the more complex tasks to accommodate non-expert participants, they would unlikely be representative of real-world tasks, possibly compromising the extrapolability and applicability of the results.

The need to use experts is even more glaring when it comes to collecting subjective metrics, as non-expert participants would be unable to provide relevant insights on the impacts of the tested methods and technologies on dam safety control's daily activities.

Another relevant methodological limitation relates to how the user study tasks were structured. In particular, while the task with higher complexity (TC) was tested across a multitude of conditions, including multiple levels of graphic detail and data indirection, tasks with lower and medium levels of complexity (TA and TB) only varied with respect to devices and modes. This limitation implies that assumptions concerning graphic detail and data indirection variations made from this study are limited to higher complexity analysis tasks.

Such limitation derives from time constraints regarding the entire duration of each test session, which we wanted to restrain to a feasible duration of no more than 60 minutes. So we opted for using tasks TA and TB for a higher-level analysis and task TC for a lower-level analysis by introducing its four extra variations (C-HDLI, C-LDLI, C-HDHI, C-LDHI).

Another methodological limitation concerns the comparability of the variations in environmental visual elements presented to participants. Indeed, as we mentioned and can be seen in Table A.3, there were some differences between the type of elements shown for the three modes. While in the PC mode, the dam structure was represented alone, over a solid colored background, for the AR, the dam structure was represented superimposed to reality using video passthrough of the surroundings. Whereas these two modes only differed in what concerns the background, the VR mode had other extra visual elements, like the terrain surrounding the dam and the sky.

The rationale behind allowing these differences, instead of having exactly the same visual elements across modes, was related to the intention of providing the user with the most common experience each specific mode would typically offer. As such, we opted for not 'handicapping' the VR experience by removing the elements required for an experience that would transmit an adequate sense of presence.

Moreover, while these elements helped the VR experience immersiveness, they would likely be detrimental in providing a representative AR experience to the participant. These additional elements would occlude the real world, hindering one of the strengths of AR (the ability to see the object of analysis without losing perception of the surroundings). And for the baseline PC mode, we wanted to keep the experience as close to the desktop software typically used at the CDD, at LNEC, like *GestBarragens* (which was discussed in Section 6.2).

While possibly having a detrimental effect on the uniformity of the experience, we believe that the advantages of our choice in terms of offering a more realistic, representative experience for each mode in the scope of the objectives of our study, outweigh the disadvantages.

Chapter 7

Guidelines

In this chapter, we present a set of general guidelines for supporting the development of immersive situated applications for dam safety control. These guidelines cover the sequential stages that typically make up the development of an application. The addressed stages are the following: conceptualization, design, implementation, testing & evaluation, and integration. In addition, we carry out a general discussion on costs and benefits.

Note: This set of guidelines was established based heavily on the work carried out by Verdelho Trindade *et al.* [160], the systematic bibliographic review conducted by Verdelho Trindade *et al.* [161] and the results pertained in Chapter 6.

7.1 Conceptualization

It is at the conceptualization stage that the developing team has the opportunity to clearly define the specificity of the dam safety control problem that the application aims to address. In that scope, they should identify, even at this early stage, which aspects of XR technologies, modalities, and concepts better fit the specific needs.

In that framework, the XR targeted hardware range should be chosen carefully so that it will serve the central purpose of the application (training, analysis, or collaboration) adequately, ensuring that the devices chosen will not be a hindrance. To that extent, factors such as comfort, functionality, and appropriate ruggedness for the characteristics of the environment (or environments) where the application will be used must be considered. Besides being adequate for the environment, the hardware should also be appropriate for the specific activity in which it will be used. For example, an AR-powered tablet like the one used in Section 4.1 will likely not be the wisest choice in an *on-site* dam safety control task that requires free hands like structural sensor deployment and calibration.

As we saw in Section 6.2, choosing XR hardware and modalities in line with the work setting can deliver clear experiential advantages. Dam-safety experts consistently felt more immersed and engaged with the AR and VR versions of the prototype than with the more familiar desktop tool, yet a prolonged headset use could become uncomfortable. As such its fundamental to attend to the balance between the richer experience achieved with head-mounted XR display against ergonomic and context-of-use constraints when defining an application's scope and target devices.

As we have seen in Chapters 4 and 5, the requirements for an *off-site* application are reasonably different from those of an application that will target *on-site* environments. Even inside each of these environmental use contexts, there are significant differences in the specificity of each visualization modality. Indeed, as we have seen in Chapter 6, *e.g.,* AR and VR for *off-site* data analysis have substantial differences in their strengths and weaknesses in regards to analytics performance and user experience.

The characteristics of the applications' target users should be kept in mind throughout the conceptualization process (and far beyond). While the specifics of *e.g.,* the UI tailoring to serve the target audience better will be detailed later in the development process, it is fundamental to have user demographics present during conceptualization. The dam safety control stakeholders (and potential target users) list is vast: dam operators, maintenance technicians, safety inspectors, control room technicians, dam safety regulators, environmental compliance officers, water resource managers, downstream residents, and, of course, engineers (civil, structural, geotechnical, hydraulic), to name a few.

The possible synergies between XR and existing computational procedures and technologies within the dam safety control scope should also be considered. An XR application can excel in every aspect, but its adoption will be unlikely if it ignores existing hardware realities (that users have relied on) and established practices.

7.2 Design

In the design stage, developers will define how the XR application will look, feel, and work to support the specific functionality previously conceptualized that will address a particular dam safety control problem. In that scope, the details of the XR application's appearance, user experience, and features must be designed.

A core design aspect is the definition of the immersive environment where the user interaction will take place. It consists of *e.g.,* the 3D assets that will be overlaid to the real world in AR applications or full virtual 3D worlds where users will be immersed, in the case of VR applications. As we have discussed in Sections 6.2.2 and 6.3.3, the visual detail of

3D assets, namely of the representation of the physical referent, has a significant impact on the application's performance and user experience. In that scope, 3D elements with rich textures are preferable to flat-shaded elements.

For dam safety control targeted situated environments, there are four environmental components, each with its particular challenges, that are frequently addressed: the dam model, the surrounding landscape, including the terrain, the water bodies, and the sky. While VR proxsituated applications typically include all of these components (as exemplified in Sections 4.2, 4.3 and 4.4), AR proxsituated ones, usually only include some of these components, in order to take advantage of the real world passthrough (as exemplified in Chapter 5 for the AR mode in the *DamXR* displacements visualization application). Furthermore, for immediate situated AR applications, these components may not even be necessary, as exemplified in Section 4.1, where the only 3D elements represented over the real dam were the sensor networks.

Data representation is another important visual component for dam safety control situated applications, especially those focused on dam data analysis. As we have seen in Sections 6.2.4 and 6.3.4, the way the developer designs data representation will likely have a significant impact on the application's performance and user experience. Moreover, as previously discussed, data representations with lower spatial indirection (overlaid directly on the referent) are preferable.

Richly textured models and data overlaid directly on the dam instead of in detached panels, should be favored. As we have seen in Section 6.2, participants navigated and interpreted scenes with realistic surfaces more confidently, and they found over-referent data representation more intuitive than comparable information shown in floating charts. As such, high visual fidelity coupled with low spatial indirection can help users grasp complex structural conditions quickly and with fewer misunderstandings.

Another core aspect at this stage is UI design. The UI should be carefully structured in order to provide the user with an accessible and efficient way to access the main features of the application. In that scope, aspects such as defining user interface diegetic elements (elements integrated into the virtual world) and non-diegetic elements (elements overlaid on the user's view) must be considered. An adequate UI design will contribute to a better user experience, leading to accessible, comfortable, and engaging applications [160].

Interaction design [67] is the third core aspect at this stage. It defines the main interaction methods and techniques that will be used in the scope of the application. These will determine how users interact *e.g.,* with the UI and how they select and manipulate data representations. They also establish how users locomote from one place to another inside the virtual environment, as exemplified in Section 5.3.

In the scope of user interaction, XR technologies are frequently paired with non-traditional interaction devices and means, like XR controllers (Figure 6.1, right) or hand gestures tracking. These typically provide a more natural interaction than the traditional keyboard and mouse. Other frequent means of interaction in XR include voice commands and gaze-based interactions.

The design of XR dam safety control situated applications should be an iterative process, enabling the gradual refinement (and testing using low and high-fidelity prototypes) of the core elements' characteristics. The main goal of this process is to successively improve and scrutinize critical aspects of the design before the implementation starts, saving valuable time and resources.

7.3 Implementation

In the implementation stage, the conceptual and design plans are executed to create the actual application. It is at this stage that the correct choice of graphical engines, programming languages, SDKs, and specialized frameworks like the *DamXR* framework, described in Chapter 5 can be decisive in successfully implementing the intended features.

The development languages and tools will translate ideas and designs into a functional XR dam safety control situated application. The first of these aspects is the selection of the programming language. The *C#* and *C++* languages are examples of some of the most currently used for developing XR applications. Their popularity for such purposes is largely due to them being the primary languages supported by *Unity* and *Unreal*, two leading graphical/game engines. Opting for one or the other of these graphical engines and languages should ideally be based on the application requirements in terms of compatibility and performance but also on the development team's familiarity with those tools [160]. Examples of applying this criterion can be found in Chapters 4 and 5.

Much of the implementation process focuses on developing the immersive environment. This process involves modeling or sourcing the 3D elements that will be part of the environment (*e.g.,* the dam or the terrain). While, as we have seen in Section 4.3, higher levels of visual detail result in performance and user experience gains, the quality of such elements should be balanced with the performance and accuracy requirements not to compromise a fluid experience.

Computer graphics optimization strategies are paramount for obtaining a higher visual detail without compromising graphical performance. A good example of such strategies is the *DamXR* framework abstraction described in Section 5.10, which is focused on real-time dynamic level of detail rendering [127] for large terrain representation in XR environments.

The implementation of XR interaction is another fundamental factor. It includes the development of aspects such as locomotion and direct interaction with virtual objects. Such interaction includes the selection of dam components. An example is the raycasting selection mechanism of specific dam sensors installed in the dam structure, described in Section 4.2.

Implementing interaction mechanisms should consider the specificities of XR modalities. In VR, for example, selection and locomotion should be configured with motion sickness prevention in mind. Moreover, in immediate situated AR applications, adequate tracking precision strategies, like the ones exemplified in Section 4.1, should be adopted in order to provide model stability and thus adequate selection precision within the AR environment.

Dam data sources, like SHM databases, should be efficiently integrated into applications to provide fast and precise data representation within the XR environment. With that purpose, real-time data processing and visualization algorithms can be considered in some situations. In others, some level of data pre-processing is required where complex calculations are needed to obtain the relevant derived measures that will be represented.

As we saw in Section 6.2, performance-minded implementation choices, using detailed meshes and textures, binding live data to geometry, and offering direct controller-based manipulation made a practical difference for a specific structural data analysis use case. Variants built on these techniques ran fluidly in headsets and let experts carry out analyses with distinct levels of complexity. Nevertheless, the implementation of simpler assets or the combination of panel data display with embedded data may be the most adequate for other specific dam safety control use-cases.

7.4 Testing & Evaluation

Extensive testing is needed before the application can be put into production and integrated into dam safety control processes. Testing procedures allow developers to identify usability and performance flaws, validate interaction mechanics, and assess the comfort and ruggedness of the chosen XR hardware in representative real-world dam safety control tasks.

An important part of those testing procedures is functional testing [45], where the application's features are evaluated to ensure they work as intended. Functional testing includes aspects such as interaction, locomotion, and UI stability [160]. It also includes validating other aspects, such as accurately representing relevant virtual objects, namely the dam structure in the immersive environment. Furthermore, it is used to evaluate the realism of the simulation of dam-related physical phenomena and other dynamic environmental processes. An example of the former is the dynamic representation of the water level variations in upstream reservoirs addressed in Section 5.9. An example of the latter is the day-night and seasonal cycle simulation addressed in Section 4.3.

Another relevant step in this stage is usability testing [65] with end-users [160]. This type of testing enables the assessment of the user experience. It serves to determine how easily and effectively users can interact with the XR applications. It is critical for identifying UI issues, detecting accessibility barriers, and validating the overall design decisions.

Performance testing [49] is another important process at this stage [160]. It is directed at evaluating the application's performance within the targeted hardware range. It is used for detecting *e.g.,* frailties in graphical performance, which may lead to a low frame rate and result in accessibility and usability problems like motion sickness.

In addition to being carried out with end users, the testing procedures should also take place in real-world environments in the context to which the application is directed (*e.g., on-site* or *off-site*). This procedure aims to ensure that the application will perform as designed in the environment, conditions, and activities it was designed for. A relevant example of this procedure is the testing environment where our user study, described in Chapter 6, was carried out (an actual office where engineers and technicians perform their daily tasks). Another example is the field testing described in Section 4.1, where the application's performance was evaluated and calibrated according to the different luminosity and shadow coverage found on-site throughout the day.

Chapter 6 shows an example of a multilayered evaluation strategy with standard usability scales, custom-designed user experience questionnaires, and objective metrics acquisition. Within such a strategy, telemetry captured through *DamXR Telemetry* was fundamental to reveal where the application excelled, where effort or comfort still lagged, and which variants actually improved task execution. The lack of context-realistic testing, or using questionnaires alone, would have led to many of those insights remaining hidden.

7.5 Post-implementation Integration

Integrating the new application with the existing dam safety control workflows should be executed as a phased roll-out [160]. Such an approach enables performance monitoring and user feedback for each phase. In that scope, user training should be carried out as early as possible in the integration process. Feedback mechanisms should also be implemented in these training stages so that their effectiveness can be assessed [146]. By helping identify issues like technical problems, this feedback can be used as a base for updates to the XR application.

Training protocols should be developed to make it easier for users to transition from traditional dam safety control methods, such as desktop PCs to XR-based methods. The use of device-agnostic applications plays a significant role in that transition. They enable users to adopt the most adequate device for a specific context, maintaining the same UI. Device-agnostic applications can potentially counter adoption resistance by providing an easy transition between devices and visualization modalities. The set of UI and interaction abstractions offered by the *DamXR* framework, described in Chapter 5 can facilitate the implementation of such applications.

Training sessions should focus initially on general XR usage aspects [181] and later on the XR-powered dam safety control skills that the trainee is expected to acquire [93]. In that scope, training sessions should be role-oriented, in the sense that the features in which engineers are trained (*e.g.,* more complex data analysis) will differ from the ones observation technicians are trained in (*e.g.,* sensor localization). Hands-on training [85] is also paramount for the smooth adoption of the application [160]. In that context, training in real-world scenarios, such as *on-site* monitoring, should occur.

Section 6.1.4 includes an example of an initial and brief hands-on session for seasoned dam engineers to learn the basics of the application. Moreover, as described in Section 6.2.8, users' perception of the usefulness and practicability of XR increased substantially after the session. This shift in perception supports the importance of a phased roll-out strategy with targeted training and early feedback loops to help users experience tangible benefits quickly, smoothing the path from traditional desktop workflows to XR-enabled practice.

Safety and ergonomics training should also be carried out to prevent accidents resulting from the incorrect use of XR technology. In that scope, training sessions should address existing safety features integrated into the hardware itself, such as anti-collision virtual boundaries like *Oculus' Guardian System* [160].

The effective impact of the application on dam safety control processes' performance should also be measured. The resulting data can be used to tweak the application's features further and establish an update roadmap, which will structure future expansions of the application [160].

7.6 Balancing Costs and Benefits

Institutions and companies typically take into account the costs of investing in new means for improving existing processes and the effective return generated by those improvements. In that sense, carrying out cost-benefit analyses before proceeding with those investments is common practice.

For the development of in-house XR dam safety control situated visualization systems, costs are generally associated with the hardware, software [112], data and man hours needed for the different stages, including conceptualization, design, implementation, testing, training, and integration. The returns generally result from increased operational efficiency [142] (which ultimately can be related to the increase in lifespan of dams) and safety [124].

The acquisition of XR devices (*e.g.,* headsets and mobile touch devices), represents a substantial portion of the initial setup costs. Hardware costs associated with application development often include specialized equipment for collecting spatial data for building 3D models. Examples of this hardware include UAVs for photogrammetry and LiDAR scanners [94]. However, due to the higher costs of such specialized equipment, 3D data acquisition and modeling are often outsourced to third-party companies.

Besides equipment, development costs can also include software licenses for XR development tools, plugins, SDKs, frameworks, and 3D assets. An example of the need for advanced computer vision SDKs for accurate AR tracking is exemplified in Section 4.1, where the *Vuforia* tracking engine was used.

The base software development environments are typically integrated with graphical/game engines, as is the case with *Unity* and *Unreal*. The costs for licensing these engines should also be taken into account.

Another set of costs that should be considered when carrying out a cost-benefit study are costs associated with the post-implementation integration stage. These include training users and creating documentation and training materials.

Concerning the possible benefits of XR-enhanced processes in dam safety control, these include the already mentioned increase in operational efficiency. They also include possible improvements in safety resulting *e.g.,* from the possibility of using XR systems for enabling remote visual inspections. Such mechanisms reduce the need for engineers and technicians to be physically present at the dam site, reducing their exposure to possible *on-site* hazards. Remote visual inspections can also reduce the costs related to traveling to the dam locations [32].

Chapter 8

Conclusions and Future Work

In this chapter, we conclude this dissertation. We start by providing a brief overview of the work developed. We then present the main conclusions that can be drawn from the work developed. Furthermore, we address possible future research paths that could be pursued based on the outcomes of this dissertation.

8.1 Thesis Overview

The motivation for conducting our research came primarily from the existence of a gap in how current structural data visualization is carried out in the context of dam safety control. Dam engineers and technicians currently rely on specialized desktop software running on PCs equipped with 2D screens. For analyzing the effect of *e.g.,* structural strains, stresses, and displacements in dams' structures, they mainly use conventional charts. While these offer abstractions for the early detection of structural problems, they are not ideal for contextualizing the abstracted data with the physical features of the dam. Such a gap may hinder the identification of the physical causes behind those structural problems.

While nothing provides a more accurate spatial awareness of the structures' features than standing in front of the actual dam, such a scenario is impractical, as dams are often located in remote locations, and dam data analysis is typically carried out off-site. And while observing the data without contextualizing it with the dam is not ideal, looking at the real dam without contextualizing it with the data is equally problematic in an analysis setting.

Based on these considerations, we wanted to know if immersive analytics could help fill this gap. In our research, we explored how situated analytics concepts could be used to contextualize data better and improve structural data visualization performance and user experience. And because dam data analysis activities are typically carried out off-site, we focused on using *proxsituated* analysis and visualization.

We set as the main objective of our work to study the application of immersive *proxsituated* methods to dam safety control for contextualizing structural data with the physical structure of the dam. We had the end goal of understanding if these methods would indeed improve user experience and analytics performance. We also wanted to know what particular properties of *proxsituatedness* would be more relevant for achieving this goal. We focused on two properties we identified as being especially relevant: the visual detail of the physical referent representation and the data representation indirection. We aimed to experiment with different variants of these two properties to determine which combination would result in greater benefits. Furthermore, we wanted to analyze how these variants would perform using two types of XR modality: AR and VR. We also studied the variants in conventional desktop PC, which served as a baseline for our studies.

The identification of the specific objectives and goals mentioned previously resulted from a long exploratory process with different XR modalities and methods. This exploratory work prompted the development of a set of application prototypes for dam safety control visualization and analysis, which used distinct XR modalities and dam datasets.

In that scope, we first started by exploring immediate situated methods. In particular, we studied the use of XR to enhance *on-site* visualization. This process led to the development of *DamAR* , an AR application that could superimpose the location of sensors directly over the real dam. It could also display the structural data registered by those sensors. This prototype ran on a tablet and could be used to assist technicians and engineers in the inspection of dams.

The following step consisted of building on the lessons learned from experimenting with AR *on-site* and trying to understand how we could adapt the principles to *off-site proxsituated* visualization. With that objective, we explored the process of effectively modeling the dam and surroundings to develop a realistic experience. Such experience should mimic the *on-site* experience as closely as possible. This exploratory process resulted in the development of *DamVR* , a VR prototype which would offer a simulation of the actual dam and could superimpose to the model of the dam, the location of sensors, and the structural data registered by those sensors.

This prototype ran on a VR headset and could be used by engineers and technicians for exploring time-dependent structural data *off-site*, contextualized with a representation of the dam. At this phase, we used higher data indirection (floating panels with charts) and higher levels of visual detail. While we improved visual detail by using photographic textures, we did not fully explore other aspects of visual detail, such as realistic lighting, atmospheric effects, and other post-processing effects.

Based on the observations made in the previous work, we pondered whether increasing the level of visual detail would result in an improved user experience, including a better sense of presence. Considering that, we next decided to explore the use of increased levels of visual detail. In particular, we wanted to understand if it was practical or even feasible to use photorealistic graphics in *proxsituated* VR environments. With that objective in mind, we used high-resolution textures, coupled with realistic lighting and shadows, as well as highly detailed models of the dam and surrounding terrain to build a proof-of-concept VR environment. This prototype allowed users to carry out a realistic, immersive tour around the dam structure and surrounding environment.

Next, we also wanted to address the use of lower levels of data representation indirection. With that objective in mind, we explored data representation directly superimposed on the dam structure model. We focused on the use of animated 3D meshes, textured with heatmaps. This study included the development of an immersive *proxsituated* prototype for analyzing observed and computed structural displacements as well as modes of vibration directly overlaid to a photorealistic representation of a dam. This application used a mixed level of visual detail and lower data representation indirection.

This situated analytics exploration process of various levels of situatedness, using different modalities of XR, distinct levels of visual detail, and data representation indirection, culminated with the development of a user study that could effectively meet our proposed research objectives. With that purpose, we developed the *DamXR* framework and the *DamXR* displacements visualization application. The former is a framework directed at supporting the development of dam safety control *proxsituated* applications. The latter is an XR prototype, built on top of the *DamXR* framework, for *proxsituated* analysis of structural dam safety control data. The prototype had the capability to run in multiple modes (AR, VR and desktop/PC mode) and alternate the analytics environment between higher and lower levels of visual detail and data representation indirection. The *DamXR* application was used to support an extended user study where the above-mentioned properties were tested and compared.

Based on the general methodologies introduced by the *DamXR* framework, we decided to further explore the application of *proxsituated* methods to areas other than structural analysis/visualization. In that sense, we applied those methodologies to the development of *GalleriesVR* a *proxsituated* application for the immersive exploration of dam galleries. We also explored the application of the *DamXR* framework to flood data analysis, with *FloodVR* a *proxsituated* prototype application for the immersive simulation of flooding during dam peak discharges. These two applications use a higher level of visual detail and lower data representation indirection.

We also wanted to make the results from our user study and the hands-on *know-how* resulting from the development of a rather long series of prototypes actionable. With that objective, we compiled a set of guidelines that systematizes what we considered are the most adequate methods and practices for the different stages of development of dam safety control immersive, *proxsituated* applications.

8.2 Conclusions

The results obtained from the studies carried out in the scope of this thesis provide valuable and actionable insights for supporting future research and the development of dam safety control immersive, *proxsituated* applications.

We first started by presenting the background concepts necessary for understanding the domains where this dissertation focuses. Those domains included extended reality, immersive analytics, situated analytics, and its *proxsituated* modality but also the area where these were applied, namely dam safety control.

The next step consisted of presenting and discussing previous scientific work related to our thesis theme. We then described the phased exploratory process that was carried out to understand the virtues of immersive situated analytics in the scope of dam safety control. That process included the development of a series of studies and prototypes for experimenting with distinct modalities of situated visualization. This process culminated with the development of a user study, supported by the implementation of the *DamXR* framework and the *DamXR* displacements visualization application.

The *DamXR* framework (and application) implementation and detailed characteristics were addressed before presenting a set of guidelines aimed at the development of situated visualization applications for dam safety control. These guidelines addressed the several stages of development and also included a brief consideration regarding the relation between the costs and benefits of implementing situated applications in that domain.

The user study enabled us to answer the research questions proposed in this dissertation and achieve its main goals. The results from this study allowed us to understand more about the weak and strong points of each of the tested modalities and variants.

Our findings show that using *proxsituated* environments for dam data analysis has non-negligible advantages in the studied conditions over its PC baseline counterpart. Indeed, the XR modes corresponded to a substantial decrease in task completion times but also an increase in the task success rate for some of the tested variants. Regarding user experience, participants found the XR modes more engaging and satisfactory, even though they use PCs in their everyday professional activity.

The differences between the two addressed XR modalities, AR and VR, despite being less substantial than the ones found between XR and PC, still allowed us to acquire valuable insights. While performance metrics differences were only significant for completion times, their user experience characteristics were more disparate. Participants found VR naturally more immersive but also more engaging. However, they considered AR to be more comfortable, requiring a lower perceived effort and better for clearly presenting data.

Concerning the variations in the level of visual detail of the objects integrated into the applications' environment, significant differences were also found between the use or absence of photographic textures. Both AR and VR reported lower completion times for the textured variant. However, in the PC mode, task completion times were lower for the non-textured version. This opposite tendency between the XR modes and PC means that for the latter, the use of textures actually got in the way of completing the tasks. Such a result might be related to the differences in perception offered by 2D screens and the stereoscopic visualization offered by headsets. Nevertheless, further research would be needed to determine the exact reason behind this disparity. It should be noted that the tendency observed in the XR modes is in line with the increase in the participant's perception (before and after the tests) regarding the advantages of using realistic textures in digital models of dams (Table B.1, question #6).

In regard to the comparison between distinct levels of data representation indirection, substantial performance differences were found between the representation of data over the referent (lower indirection) and using floating panels with conventional charts (higher indirection). All the modes registered lower average task completion times for lower data representation indirection. The smallest differences were registered in the PC mode, and the biggest differences were recorded for VR. The task success rate also registered significant differences across modes. However, while for the XR modes, lower data indirection corresponded to higher success rates, for the PC mode, success rates were higher for higher data indirection.

Overall, data representation indirection seems to have a much more significant impact on analysis performance (time and success) than visual detail. When analyzing the variants resulting from the combined influence of data indirection and visual detail, the mode with the lowest average completion times and the highest success rate is the HDLI variant (lower data indirection and higher visual detail). Furthermore, from the tested modes, VR registered the lowest overall completion times, with the HDLI variant and AR registered the highest overall success rates for the HDLI variant.

8.3 Future Work

In this work, we explored just a narrow portion of the possibilities opened by immersive technologies and situated visualization in the domain of dam safety control. Even at a lower level, we only effectively explored a subset of the *proxsituated* concepts and relationships in that domain: the variation in spatial indirection together with the type of digital data representation, the use of distinct levels of detail, and the use of digital proxies [138]. However, while our study also implied concepts like temporal indirection (*e.g.,* the tasks included the visualization of structural conditions in the past) or representation scales (*e.g.,* through the non-egocentric visualization of the dam structure), these aspects were not explicitly targeted in our user study. The study of the isolated or combined impact of such aspects provides ample opportunities for future research.

At a higher level, while we studied the impact of XR *proxsituated* methods in dam structural data analysis, these methods may have great potential in other facets of dam safety control. Indeed, as we have seen in Chapter 2.4, its purpose extends well beyond that scope. Indeed, structural safety is only one facet of dam safety control, which includes aspects such as hydraulic-operational safety, environmental safety, geotechnical safety and the implementation of emergency plans for downstream population safety.

Dam safety control also encompasses other activities that can be explored with *proxsituated* methods, such as hydro-environmental outreach initiatives concerning the functional and hydro-environmental facets of dams. While we have addressed the hydro-environmental theme with our flood visualization prototype (*FloodVR*), this system's main purpose is flood data analysis, not outreach initiatives.

The exploration of the usefulness of these methods for awareness of the environmental importance of dams and their role in the conservation of water resources also creates pathways for future research. Indeed, as we have seen in our study, *proxsituated* environments can offer increased engagement.

In addition to *proxsituated* visualization, immediate situated methods also afford opportunities for dam safety control. As we have seen with our *DamAR* prototype, they can be used for visualizing structural data directly superimposed on the actual dam. However, the possibilities for future research on immediate situated methods extend much beyond *on-site* data visualization. They can be directed *e.g.,* to such purposes as training field technicians.

Regarding future paths for the improvement of the *DamXR* framework, we plan to continue working on increasing its functionality and usefulness. One of the aspects that we are going to address in the very near future is the support for collaborative visualization. Collaboration is one of the cornerstones of immersive analytics and thus situated and *proxsituated* visualization. We believe that such a possibility would be of great usefulness for *e.g.*, project discussion meetings around a single 3D visualization, as mocked up in Figure 8.1.

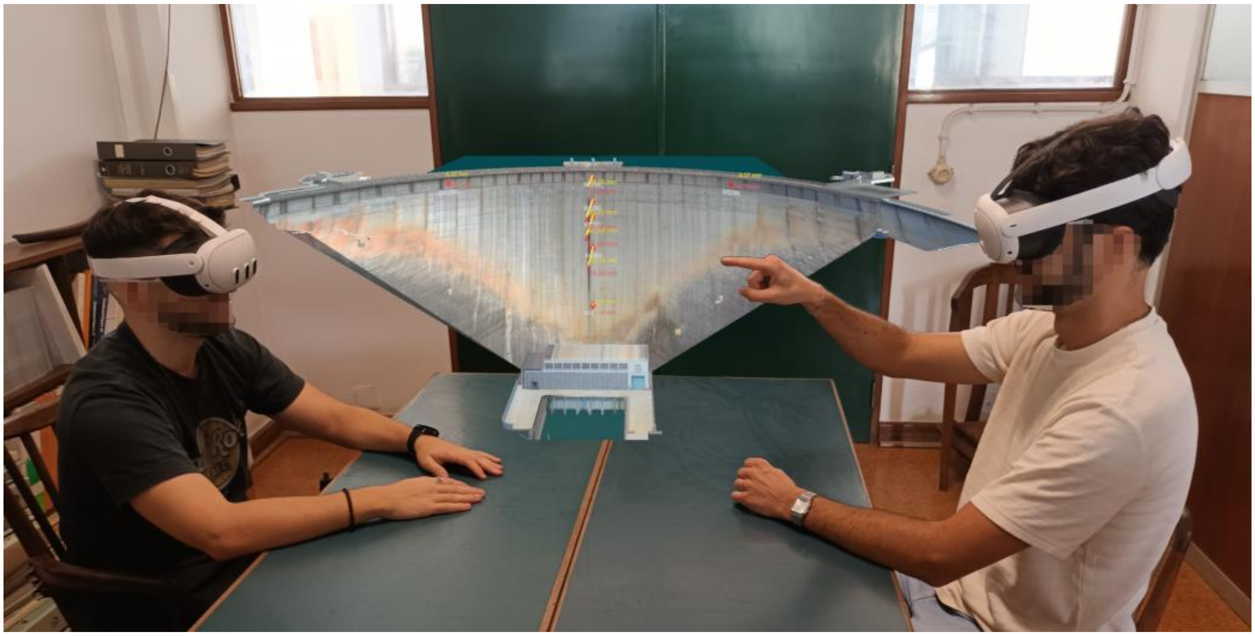


Figure 8.1: Collaborative visualization is planned to be supported by the *DamXR* framework in the near future. Such possibility can be useful for *e.g.*, project discussion meetings around a single 3D visualization (*mockup*)

8.4 Final Remarks

As a final remark to this document, we can say that we have achieved the objectives that we initially proposed for this dissertation. We have validated our thesis that immersive *proxsituated* visualization can, in fact, be used for improving user experience and analytics performance by contextualizing structural data with the physical structure of the dam.

We hope that the outcomes of this work can serve as base for future research endeavors in the field of situated visualization. We also aspire that our findings will help researchers and dam engineering professionals carry out a more informed development of studies and applications.

Appendix A

User Study Tasks

Task	Task text
A	Determine the designation of the [first|second|third] geodetic mark from the top on the center section of the dam. (‘*Determine a designação da [primeira/segunda /terceira] marca geodésica a contar do topo na secção central da barragem.*’)
B	Determine the value of the [observed|calculated] displacement at the [first|second|third] geodetic mark from the top in the central section of the dam, on the date YYYY-MM-DD. (‘*Determine o valor do deslocamento [observado/calculado] na [primeira/segunda/terceira] marca geodésica a contar do topo na secção central da barragem, na data AAAA-MM-DD.*’)
C	For the date YYYY-MM-DD determine for which of the following geodetic marks of the central section the observed displacement is [greater|smaller] than the calculated displacement: [first|second|third] mark from the top, [first|second|third] marks from the top. (‘*Para a data AAAA-MM-DD determine para qual das seguintes marcas geodésicas da secção central o deslocamento observado é [superior/inferior] ao deslocamento calculado: [primeira/segunda/terceira] marca a contar do topo, [primeira/segunda/terceira] marca a contar do topo.*’)

Table A.1: Tasks presented to the participants (the English translation followed by the original, in Portuguese language) when testing the *DamXR* application.

	Visual Detail		Data Indirection	
Task	Textured	Flat shaded	Data over referent	Data in panels
A	✓		✓	
B	✓		✓	
C-HDLI	✓		✓	
C-LDLI		✓	✓	
C-HDHI	✓			✓
C-LDHI		✓		✓

Table A.2: Visual detail and data indirection characteristics for tasks A and B and for each variation of task C, when testing the *DamXR* application.

Mode	Dam structure	Terrain	Water	Sky	Passthrough	Solid color background
PC	✓		✓			✓
AR	✓		✓		✓	
VR	✓	✓	✓	✓		

Note: The representation of bodies of water is made to a lesser extent in AR and PC than VR

Table A.3: Visual elements included for each mode of the *DamXR* application in addition to the data representation and interface menus.

Appendix B

User Study Questionnaires

#	Question
1	I have the impression that virtual reality can be useful for my activity. ('*Tenho a ideia de que a realidade virtual pode ser útil para minha atividade.*')
2	I have the impression that augmented reality can be useful for my activity. ('*Tenho a ideia de que a realidade aumentada pode ser útil para minha atividade.*')
3	I think it is impractical to use virtual reality glasses in my professional context. ('*Penso que é pouco prático usar óculos de realidade virtual no meu contexto profissional.*')
4	Virtual and augmented reality allows you to have a better spatial perception of 3D representations of data, compared to using a computer screen. ('*A realidade virtual e aumentada permite ter uma melhor perceção espacial de representações 3D de dados, em comparação com o uso de um ecrã de computador.*')
5	Visualizing data overlaid on a digital 3D model of a dam has no advantages over representing that data in graphics. ('*A visualização de dados sobrepostos a um modelo 3D digital de uma barragem não tem quaisquer vantagens sobre a representação desses dados em gráficos.*)'
6	In the context of data analysis, the use of digital models of dams with realistic textures (photographic textures) has advantages over the use of the same models without photographic textures. ('*No âmbito da análise de dados, a utilização de modelos digitais de barragens com texturas realistas (texturas fotográficas) tem vantagens sobre o uso dos mesmos modelos, sem texturas fotográficas.*')
7	When analyzing data related only to the structure of a dam, the use of digital models that include the terrain and other elements surrounding the dam do not offer advantages over models that include only the dam structure. ('*Na análise de dados relacionados apenas com a estrutura de uma barragem, o uso de modelos digitais que incluam o terreno e outros elementos circundantes à barragem não oferecem vantagens sobre modelos que incluam apenas a estrutura da barragem.*')

Table B.1: Questionnaire questions (the English translation followed by the original, in Portuguese language) used to assess the perception of users regarding XR technologies, before and after using the *DamXR* application. The questionnaire used a a five-level *Likert scale* for agreement (1: strongly disagree and 5: strongly agree). Some of the questions used positive phrasing and others negative in order to reduce response bias.

#	Question	Aspect
1	I felt immersed in the application. ('*Senti-me imerso(a) na aplicação.*')	Immersiveness
2	The experience was boring and not very captivating. ('*A experiência foi aborrecida e pouco cativante.*')	Engagement
3	I felt satisfied using the application. ('*Senti-me satisfeito(a) a usar a aplicação.*')	Satisfaction
4	Using the application involved a high mental effort. ('*O uso da aplicação implicou um esforço mental elevado.*')	Perceived Effort
5	The data was presented clearly. ('*Os dados foram apresentados de forma clara.*')	Data Clarity
6	The application is unintuitive. ('*A aplicação é pouco intuitiva.*')	Intuitiveness
7	I was able to concentrate on tasks without being distracted by unnecessary interface elements. ('*Consegui concentrar-me nas tarefas sem ser distraído(a) por elementos desnecessários da interface.*')	User Focus
8	I felt physically uncomfortable using the app. ('*Senti-me fisicamente desconfortável a usar a aplicação.*')	Comfort and Physical Well-Being
9	The application responded quickly to my actions. ('*A aplicação respondeu de forma rápida às minhas ações.*')	Feedback and Responsiveness
10	I would not use the application again. ('*Não voltaria a usar a aplicação novamente.*')	Post-Use Impact

Table B.2: Questionnaire questions (the English translation followed by the original, in Portuguese language) used to assess the usability of the three modes of the prototype: PC, AR and VR. One of these questionnaires was filled out by participants for each of the modes to be able to compare usability in each of these modes. The 10 questions used a five-level *Likert scale* for agreement (1: strongly disagree and 5: strongly agree). Half of the questions used positive phrasing and the other half negative in order to reduce response bias. The mapping of each question with the usability aspect targeted is also included.

#	Question
1	I think that I would like to use this system frequently. (‘*Acho que gostaria de utilizar este sistema com frequência.*’)
2	I found the system unnecessarily complex. (‘*Considerei o sistema mais complexo do que necessário.*’)
3	I thought the system was easy to use. (‘*Achei o sistema fácil de utilizar.*’)
4	I think that I would need the support of a technical person to be able to use this system. (‘*Acho que necessitaria de ajuda de um técnico para conseguir utilizar este sistema.*’)
5	I found the various functions in this system were well integrated. (‘*Considerei que as várias funcionalidades deste sistema estavam bem integradas.*’)
6	I thought there was too much inconsistency in this system. (‘*Achei que este sistema tinha muitas inconsistências.*’)
7	I would imagine that most people would learn to use this system very quickly. (‘*Suponho que a maioria das pessoas aprenderia a utilizar rapidamente este sistema.*’)
8	I found the system very cumbersome to use. (‘*Considerei o sistema muito complicado de utilizar.*’)
9	I felt very confident using the system. (‘*Senti-me muito confiante a utilizar este sistema.*’)
10	I needed to learn a lot of things before I could get going with this system. (‘*Tive que aprender muito antes de conseguir lidar com este sistema.*’)

Table B.3: Questions (the English translation followed by the original, in Portuguese language) of the SUS [100] standard questionnaire, used to obtain single reference scores regarding the usability of the prototype as a whole and also each of its modes: PC, AR and VR. One of these questionnaires was filled out by participants for each of the modes and also for the prototype as a whole (considering the combined use of the three modes). The 10 questions used a five-level *Likert scale* for agreement (1: strongly disagree and 5: strongly agree). Half of the questions used positive phrasing and the other half negative in order to reduce response bias.

Appendix C

Ethics and Data Protection Assessments

TÉCNICO LISBOA

Ethis Commission (CE-IST)

Ref. n.º 31/2024 (CE-IST)
Date: 18/12/2024

Name of PI: Alfredo Manuel dos Santos Ferreira Júnior

Immersive Analytics in Dam Safety Control

Prof. Alfredo Manuel dos Santos Ferreira Júnior

The Ethics Committee of Instituto Superior Técnico (EC-IST) reviewed your application to obtain ethical assessment for the above mentioned project. The following documents have been reviewed:

Ref.	Documents	Version & date
1925490	Formulario_COMISSAO DE ETICA IST_2024-04-15 .pdf Alterações para Comissão de Ética.pdf 00_consentimento_informado.pdf 01_questionario-demografico.pdf 02_questionario-usabilidade.pdf 03_questionario-sus.pdf 04_questionario-feedback.pdf Segurança de Barragens_Parecer DPO_assinado.pdf	25/06/2024

The following members of the EC-IST participated in the ethical assessment:

Name	Role in Ethics Committee	Qualification	Gender	Affiliation to IST (Yes/No)
Mário Gaspar da Silva	President	Professor	M	Y
Isabel Trancoso	Member	Professor	F	Y
Isabel Sá Correia	Member	Professor	F	Y
Fernando Borges Araújo	Member	Professor	M	N
Miguel Prazeres	Member	Professor	M	Y

This EC-IST is working accordance to ICH-GCP, Schedule Y and ICMR guidelines, the EC-IST regulation and other applicable regulation.

None of the researchers participating in this study took part in the decision making and voting procedure for this assessment.

Based on the review of the above mentioned documents, the EC-IST states a favourable ethical opinion about the request / trial as submitted.

The EC-IST expects to be informed about the progress of the study, any Serious Adverse Events occurring in the course of the study, any revision in the protocol and in the participants' information/informed consent, and requests to be provided a copy of the final report.

Prof. Mário Gaspar da Silva
President of Ethics Committee of
Instituto Superior Técnico (CE-IST)

ASSUNTO: **Estudo "Análise Imersiva de Dados no Controlo da Segurança de Barragens" – parecer Encarregado da Proteção de Dados**

DATA: **18 de outubro de 2024**

No âmbito da avaliação do estudo "Análise Imersiva de Dados no Controlo da Segurança de Barragens" realizado pelo doutorando Nuno Verdelho Trindade, sob a coordenação do Professor Doutor Alfredo Ferreira que visa estudar se (e de que forma) os ambientes imersivos de análise podem ser utilizados para melhorar a visualização de dados associados a barragens, em comparação com meios convencionais, declaro que me familiarizei com a documentação referente ao estudo (Formulário de consentimento, Questionários: Demográfico, de Usabilidade, *System Usability Scale* e de Feedback, bem como com o Pedido de Parecer dirigido à Comissão de Ética) e que considero que o estudo cumpre com os requisitos traçados pela legislação em vigor no que diz respeito à proteção de dados pessoais.

Recomendo que todos os membros da equipa com o acesso aos dados tenham as Declarações de Confidencialidade (NDA) assinadas. Do resto, não há questões a assinalar.

Weronika Figueiredo
Encarregada da Proteção de Dados, INESC ID

Anexo I ao Parecer do Encarregado da Proteção de Dados – Tratamentos de dados pessoais – caraterização

Tratamentos de dados	Recolha, registo, organização, consulta, utilização, conservação, apagamento.
Titulares de dados	Participantes voluntários do estudo – não inclui menores nem outras categorias de titulares vulneráveis
Categorias de dados	Dados demográficos (a incluir experiência prévia com tecnologia), dados de interação e dados de opinião – não inclui dados de categorias especiais. De acordo com o esclarecimento prestado pelo responsável, não vai ser possível reconhecer / identificar os titulares através das fotografias recolhidas neste contexto.
Base de licitude	Consentimento
Prazo de conservação	Apenas durante o projeto de investigação.
Decisões automatizadas	N/A
Medidas de segurança	Pseudonimização, separação lógica de dados, acesso restrito aos dados, protegido por uma password, compromisso de confidencialidade assumido pela equipa de investigação
Transferências internacionais de dados	N/A

References

[1] R. P. Abao, C. V. Malabanan, and A. P. Galido, “Design and development of foodgo: A mobile application using situated analytics to augment product information,” *Procedia Computer Science*, vol. 135, pp. 186–193, 2018, ISSN: 18770509. DOI: 10.1016/j.procs.2018.08.165.

[2] H. I. M. M. Abeynayake, R. S. Goonetilleke, A. Wijeweera, and U. Reischl, “Efficacy of information extraction from bar, line, circular, bubble and radar graphs,” *Applied Ergonomics*, vol. 109, p. 103 996, May 2023, ISSN: 00036870. DOI: 10.1016/j.apergo.2023.103996. Accessed: Feb. 1, 2025.

[3] N. Adamo, N. Al-Ansari, V. Sissakian, J. Laue, and S. Knutsson, “Dams safety: Inspections, safety reviews, and legislations,” *Journal of Earth Sciences and Geotechnical Engineering*, pp. 109–143, Sep. 2020. DOI: 10.47260/jesge/1114.

[4] D. Aelenei, L. Aelenei, and C. P. Vieira, “Adaptive façade: Concept, applications, research questions,” *Energy Procedia*, vol. 91, pp. 269–275, Jun. 2016, ISSN: 18766102. DOI: 10.1016/j.egypro.2016.06.218.

[5] F. Alallah, Y. Sakamoto, and P. Irani, “Exploring the need and design for situated video analytics,” in *Symposium on Spatial User Interaction*, Virtual Event Canada: ACM, 2020, pp. 1–11, ISBN: 978-1-4503-7943-4. DOI: 10.1145/3385959.3418458.

[6] A. Alhady, M. Alanany, Y. Khodair, S. Salem, and Y. El Maghraby, “Integrating building information modelling (bim) and extended reality (xr) in the transportation infrastructure industry,” *Advances in Bridge Engineering*, vol. 5, no. 1, p. 22, Aug. 2024, ISSN: 2662-5407. DOI: 10.1186/s43251-024-00132-6.

[7] F. J. Anscombe, “On estimating binomial response relations,” *Biometrika*, vol. 43, no. 3-4, pp. 461–464, 1956, ISSN: 0006-3444, 1464-3510. DOI: 10.1093/biomet/43.3-4.461. Accessed: Jul. 6, 2025.

[8] Y. Bai and Q. Bai, "Subsea surveying, positioning, and foundation," in *Subsea Engineering Handbook*, Elsevier, 2019, pp. 81–121, ISBN: 978-0-12-812622-6. DOI: 10.1016/B978-0-12-812622-6.00004-X.

[9] A. Bangor, P. Kortum, and J. Miller, "Determining what individual sus scores mean: Adding an adjective rating scale," *J. Usability Studies*, vol. 4, no. 3, pp. 114–123, May 2009. [Online]. Available: https://uxpajournal.org/determining-what-individual-sus-scores-mean-adding-an-adjective-rating-scale/.

[10] A. C. Bavelos, E. Anastasiou, N. Dimitropoulos, G. Oikonomou, and S. Makris, "Augmented reality-based method for road maintenance operators in human–robot collaborative interventions," *Computer-Aided Civil and Infrastructure Engineering*, vol. 39, no. 7, pp. 1077–1095, Apr. 2024, ISSN: 1093-9687, 1467-8667. DOI: 10.1111/mice.13185.

[11] V. Beatini, F. Pantilimonescu, Z. Djebbara, and M.-C. Drișcu, "Adaptive facades for emotionally enriching indoor environments," *Journal of Building Engineering*, vol. 98, p. 111 472, Dec. 2024, ISSN: 23527102. DOI: 10.1016/j.jobe.2024.111472.

[12] A. H. Behzadan and V. R. Kamat, "Interactive augmented reality visualization for improved damage prevention and maintenance of underground infrastructure," in *Construction Research Congress 2009*, Seattle, Washington, United States: American Society of Civil Engineers, Apr. 2009, pp. 1214–1222, ISBN: 978-0-7844-1020-2. DOI: 10.1061/41020(339)123.

[13] Y. Benjamini and Y. Hochberg, "Controlling the false discovery rate: A practical and powerful approach to multiple testing," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, vol. 57, no. 1, pp. 289–300, Jan. 1995, ISSN: 1369-7412, 1467-9868. DOI: 10.1111/j.2517-6161.1995.tb02031.x. Accessed: Jul. 11, 2025.

[14] M. Berger, "Egocentric sonification of continuous spatial data in situated analytics," in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, Atlanta, GA, USA: IEEE, 2020, pp. 658–659, ISBN: 978-1-7281-6532-5. DOI: 10.1109/VRW50115.2020.00180.

[15] M. Berger, A. Tagliasacchi, L. M. Seversky, P. Alliez, G. Guennebaud, J. A. Levine, A. Sharf, and C. T. Silva, "A survey of surface reconstruction from point clouds," *Computer Graphics Forum*, vol. 36, no. 1, pp. 301–329, 2017, ISSN: 0167-7055, 1467-8659. DOI: 10.1111/cgf.12802.

[16] M. Billinghurst, M. Cordeil, A. Bezerianos, and T. Margolis, "Collaborative immersive analytics," in *Immersive Analytics*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International Publishing, 2018, pp. 221–257, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_8. Accessed: Feb. 3, 2025.

[17] N. Bressa, H. Korsgaard, A. Tabard, S. Houben, and J. Vermeulen, "What's the situation with situated visualization? a survey and perspectives on situatedness," *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 1, pp. 107–117, 2022, ISSN: 1077-2626, 1941-0506, 2160-9306. DOI: 10.1109/TVCG.2021.3114835.

[18] J. Brooke, "Sus: A 'quick and dirty' usability scale," in *Usability Evaluation In Industry*, 1st, Taylor & Francis, 1996, pp. 189–194, ISBN: 0-7484-0314-0. [Online]. Available: https://www.taylorfrancis.com/chapters/edit/10.1201/9781498710411-35/sus-quick-dirty-usability-scale-john-brooke.

[19] W. Büschel, A. Lehmann, and R. Dachselt, "Miria: A mixed reality toolkit for the in-situ visualization and analysis of spatio-temporal interaction data," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, Yokohama Japan: ACM, 2021, pp. 1–15, ISBN: 978-1-4503-8096-6. DOI: 10.1145/3411764.3445651.

[20] A. T. de Castro, J. Mata, J. Barateiro, and P. Miranda, "Information management systems for dam safety control. the portuguese experience," in *Proceedings of the 54º Congresso Brasileiro Do Concreto - CBC*, Brazil: IBRACON, 2012, pp. 1–13. [Online]. Available: https://repositorio.lnec.pt/jspui/handle/123456789/1003937.

[21] T. Chen, N. Yabuki, and T. Fukuda, "Mixed reality-based active hazard prevention system for heavy machinery operators," *Automation in Construction*, vol. 159, p. 105 287, Mar. 2024, ISSN: 09265805. DOI: 10.1016/j.autcon.2024.105287.

[22] Y.-H. Cheng, S.-L. Kao, S.-D. Lee, M.-F. Yang, Y.-T. Wang, and Y.-J. Huang, "Application of virtual reality modeling to the development of a three-dimensional underwater model," in *Advances in Transdisciplinary Engineering*, M. Shafik, Ed., IOS Press, Feb. 2024, ISBN: 978-1-64368-504-5. DOI: 10.3233/ATDE240035.

[23] R. Chin, "Cabrildamvr: A photorealistic and immersive virtual reality experience," M.S. thesis, Instituto Superior Técnico, University of Lisbon, Lisbon, Portugal, 2023. [Online]. Available: https://fenix.tecnico.ulisboa.pt/cursos/meic-a/dissertacao/1972678479055772.

[24] N. Cid Martins, B. Marques, P. Dias, and B. Sousa Santos, "Extending the egocentric viewpoint in situated visualization using augmented reality," in *2023 27th International Conference Information Visualisation (IV)*, Tampere, Finland: IEEE, Jul. 2023, pp. 83–89, ISBN: 979-8-3503-4161-4. DOI: 10.1109/IV60283.2023.00024.

[25] W. S. Cleveland, "Theory and experimentation," in *The Elements of Graphing Data*, 10.[print.], Monterey, Cal: Wadsworth, 1989, pp. 241–255, ISBN: 978-0-534-03730-7.

[26] J. Cohen, "A power primer.," *Psychological Bulletin*, vol. 112, no. 1, pp. 155–159, 1992, ISSN: 1939-1455, 0033-2909. DOI: 10.1037/0033-2909.112.1.155. Accessed: Jul. 6, 2025.

[27] J. Cohen, "The analysis of variance," in *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed., New York, NY: Routledge, 1988, pp. 284–287. [Online]. Available: https://doi.org/10.4324/9780203771587.

[28] J. Cohen, "The significance of a product moment rs - the effect size: R," in *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed., New York, NY: Routledge, 1988, pp. 77–83. [Online]. Available: https://doi.org/10.4324/9780203771587.

[29] D. Cornel, A. Buttinger-Kreuzhuber, A. Konev, Z. Horváth, M. Wimmer, R. Heidrich, and J. Waser, "Interactive visualization of flood and heavy rain simulations," *Computer Graphics Forum*, vol. 38, no. 3, pp. 25–39, Jun. 2019, ISSN: 0167-7055, 1467-8659. DOI: 10.1111/cgf.13669.

[30] D. R. Cox, "The regression analysis of binary sequences," *Journal of the Royal Statistical Society Series B: Statistical Methodology*, vol. 20, no. 2, pp. 215–232, Jul. 1958, ISSN: 1369-7412, 1467-9868. DOI: 10.1111/j.2517-6161.1958.tb00292.x. Accessed: Jul. 9, 2025.

[31] M. Dabić, T. O. Posinković, J. F. Maley, B. Vlačić, G. Marzi, and S. Kraus, "Exploring the multifaceted challenges of women in engineering: A comprehensive literature review," *IEEE Transactions on Engineering Management*, vol. 71, pp. 3325–3339, 2024, ISSN: 0018-9391, 1558-0040. DOI: 10.1109/TEM.2023.3342980.

[32] J. M. Davila Delgado, L. Oyedele, P. Demian, and T. Beach, "A research agenda for augmented and virtual reality in architecture, engineering and construction," *Advanced Engineering Informatics*, vol. 45, p. 101 122, Aug. 2020, ISSN: 14740346. DOI: 10.1016/j.aei.2020.101122.

[33] A. Dean, "Experimental design: Overview," in *International Encyclopedia of the Social & Behavioral Sciences*, Elsevier, 2001, pp. 5090–5096, ISBN: 978-0-08-043076-8. DOI: 10.1016/B0-08-043076-7/00417-4.

[34] C. Dede, "Immersive interfaces for engagement and learning," *Science*, vol. 323, no. 5910, pp. 66–69, Jan. 2009, ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.1167311.

[35] C.-L. Deng, C.-Y. Tian, and S.-G. Kuai, "A combination of eye-gaze and head-gaze interactions improves efficiency and user experience in an object positioning task in virtual environments," *Applied Ergonomics*, vol. 103, p. 103 785, Sep. 2022, ISSN: 00036870. DOI: 10.1016/j.apergo.2022.103785.

[36] S. Dubel, M. Rohlig, H. Schumann, and M. Trapp, "2d and 3d presentation of spatial data: A systematic review," in *2014 IEEE VIS International Workshop on 3DVis (3DVis)*, Paris, France: IEEE, Nov. 2014, pp. 11–18, ISBN: 978-1-4799-6826-8. DOI: 10.1109/3DVis.2014.7160094. Accessed: Feb. 1, 2025.

[37] T. Dwyer, K. Marriott, T. Isenberg, K. Klein, N. Riche, F. Schreiber, W. Stuerzlinger, and B. Thomas, "Immersive analytics: An introduction," in *Immersive Analytics*, ser. Lecture Notes in Computer Science, Springer International Publishing, 2018, pp. 1–23, ISBN: 978-3-030-01388-2. [Online]. Available: https://doi.org/10.1007/978-3-030-01388-2.

[38] 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*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International Publishing, 2018, pp. 1–23, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_1.

[39] N. Elsayed, K. Marriott, R. Smith, and B. H. Thomas, "Situated analytics process and mantra," in *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, Honolulu HI USA: ACM, May 2024, pp. 1–9, ISBN: 979-8-4007-0331-7. DOI: 10.1145/3613905.3650814.

[40] N. ElSayed, B. Thomas, K. Marriott, J. Piantadosi, and R. Smith, "Situated analytics," in *2015 Big Data Visual Analytics (BDVA)*, Hobart, Australia: IEEE, 2015, pp. 1–8, ISBN: 978-1-4673-7343-2. DOI: 10.1109/BDVA.2015.7314302.

[41] N. A. M. ElSayed, R. T. Smith, K. Marriott, and B. H. Thomas, "Blended ui controls for situated analytics," in *2016 Big Data Visual Analytics (BDVA)*, Sydney, Australia: IEEE, 2016, pp. 1–8, ISBN: 978-1-5090-5272-1. DOI: 10.1109/BDVA.2016.7787043.

[42] N. A. M. ElSayed, B. H. Thomas, R. T. Smith, K. Marriott, and J. Piantadosi, "Using augmented reality to support situated analytics," in *2015 IEEE Virtual Reality (VR)*, Arles, Camargue, Provence, France: IEEE, 2015, pp. 175–176, ISBN: 978-1-4799-1727-3. DOI: 10.1109/VR.2015.7223352.

[43] N. A. ElSayed, R. T. Smith, K. Marriott, and B. H. Thomas, "Context-aware design pattern for situated analytics: Blended model view controller," *Journal of Visual Languages & Computing*, vol. 44, pp. 1–12, 2018, ISSN: 1045926X. DOI: 10.1016/j.jvlc.2017.11.001.

[44] N. A. ElSayed, B. H. Thomas, K. Marriott, J. Piantadosi, and R. T. Smith, "Situated analytics: Demonstrating immersive analytical tools with augmented reality," *Journal of Visual Languages & Computing*, vol. 36, pp. 13–23, 2016, ISSN: 1045926X. DOI: 10.1016/j.jvlc.2016.07.006.

[45] A. Elssamadisy and J. Whitmore, "Functional testing: A pattern to follow and the smells to avoid," in *Proceedings of the 2006 Conference on Pattern Languages of Programs*, Portland Oregon USA: ACM, Oct. 2006, pp. 1–13, ISBN: 978-1-60558-372-3. DOI: 10.1145/1415472.1415504.

[46] B. Ens, F. Anderson, T. Grossman, M. Annett, P. Irani, and G. Fitzmaurice, "Ivy: Exploring spatially situated visual programming for authoring and understanding intelligent environments," in *Proceedings of the 43rd Graphics Interface Conference*, vol. 1, Edmonton, Canada: Canadian Human-Computer Communications Society, 2017, pp. 156–162, ISBN: 978-0-9947868-2-1. [Online]. Available: https://dl.acm.org/doi/10.5555/3141475.3141507.

[47] B. Ens and P. Irani, "Spatial analytic interfaces: Spatial user interfaces for in situ visual analytics," *IEEE Computer Graphics and Applications*, vol. 37, no. 2, pp. 66–79, 2017, ISSN: 0272-1716. DOI: 10.1109/MCG.2016.38.

[48] K. A. Ericsson and H. A. Simon, "Verbal reports as data.," *Psychological Review*, vol. 87, no. 3, pp. 215–251, May 1980, ISSN: 1939-1471, 0033-295X. DOI: 10.1037/0033-295X.87.3.215.

[49] R. P. Esteves and M. A. Brito, "Agnostic performance testing framework," in *Proceedings of the 2023 9th International Conference on Computer Technology Applications*, Vienna Austria: ACM, May 2023, pp. 179–183, ISBN: 978-1-4503-9957-9. DOI: 10.1145/3605423.3605436.

[50] A. Fazel and A. Adel, "Enhancing construction accuracy, productivity, and safety with augmented reality for timber fastening," *Automation in Construction*, vol. 166, p. 105 596, Oct. 2024, ISSN: 09265805. DOI: 10.1016/j.autcon.2024.105596.

[51] F. Ferland, F. Pomerleau, C. T. Le Dinh, and F. Michaud, "Egocentric and exocentric teleoperation interface using real-time, 3d video projection," in *Proceedings of the 4th ACM/IEEE International Conference on Human Robot Interaction*, La Jolla California USA: ACM, Mar. 2009, pp. 37–44, ISBN: 978-1-60558-404-1. DOI: 10.1145/1514095.1514105.

[52] M. H. Fischer, N. Dewulf, and R. L. Hill, "Designing bar graphs: Orientation matters," *Applied Cognitive Psychology*, vol. 19, no. 7, pp. 953–962, Nov. 2005, ISSN: 0888-4080, 1099-0720. DOI: 10.1002/acp.1105.

[53] R. A. Fisher, "Theory of statistical estimation," *Mathematical Proceedings of the Cambridge Philosophical Society*, vol. 22, no. 5, pp. 700–725, Jul. 1925, ISSN: 0305-0041, 1469-8064. DOI: 10.1017/s0305004100009580. Accessed: Jul. 9, 2025.

[54] P. Fleck, A. S. Calepso, S. Hubenschmid, M. Sedlmair, and D. Schmalstieg, "Ragrug: A toolkit for situated analytics," *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 7, pp. 3281–3297, 2023, ISSN: 1077-2626, 1941-0506, 2160-9306. DOI: 10.1109/TVCG.2022.3157058.

[55] J. Gabel, S. Schmidt, O. Ariza, and F. Steinicke, "Redirecting rays: Evaluation of assistive raycasting techniques in virtual reality," in *29th ACM Symposium on Virtual Reality Software and Technology*, Christchurch New Zealand: ACM, Oct. 2023, pp. 1–11, ISBN: 979-8-4007-0328-7. DOI: 10.1145/3611659.3615716.

[56] "Foreword," in *Information Visualization: Proceedings, October 30-31, 1995, Atlanta, Georgia, USA*, N. Gershon and S. Eick, Eds., Los Alamitos, Calif: IEEE Computer Society Press, 1995, ISBN: 978-0-8186-7201-9.

[57] L. Given, "Situatedness," in *The SAGE Encyclopedia of Qualitative Research Methods*, 2455 Teller Road, Thousand Oaks California 91320 United States: SAGE Publications, Inc., 2008, pp. 815–816, ISBN: 978-1-4129-4163-1. [Online]. Available: https://methods.sagepub.com/reference/sage-encyc-qualitative-research-methods/n424.xml.

[58] G. J. Glasser and R. F. Winter, "Critical values of the coefficient of rank correlation for testing the hypothesis of independence," *Biometrika*, vol. 48, no. 3-4, pp. 444–448, 1961, ISSN: 0006-3444, 1464-3510. DOI: 10.1093/biomet/48.3-4.444. Accessed: Jul. 11, 2025.

[59] C. A. Goff, M. S. Atyeo, O. Gimeno, and M. N. Wetton, "Dealing with data: Innovation in monitoring and operation and maintenance of dams," *Dams and Reservoirs*, vol. 26, no. 1, pp. 5–12, 2016, ISSN: 1368-1494, 1756-8404. DOI: 10.1680/jdare.16.00011.

[60] R. Guarese, P. Andreasson, E. Nilsson, and A. Maciel, "Augmented situated visualization methods towards electromagnetic compatibility testing," *Computers & Graphics*, vol. 94, pp. 1–10, 2021, ISSN: 00978493. DOI: 10.1016/j.cag.2020.10.001.

[61] J. Ha, K. Alrayyan, and M. M. L. Alam, "Virtual reality technology for learning detailed design in landscape architecture," *Discover Education*, vol. 3, no. 1, p. 39, Apr. 2024, ISSN: 2731-5525. DOI: 10.1007/s44217-024-00123-9.

[62] J. B. S. Haldane, "The mean and variance of | chi 2 , when used as a test of homogeneity, when expectations are small," *Biometrika*, vol. 31, no. 3/4, p. 346, Mar. 1940, ISSN: 00063444. DOI: 10.2307/2332614. JSTOR: 2332614. Accessed: Jul. 6, 2025.

[63] S. G. Hart and L. E. Staveland, "Development of nasa-tlx (task load index): Results of empirical and theoretical research," in *Advances in Psychology*, vol. 52, Elsevier, 1988, pp. 139–183, ISBN: 978-0-444-70388-0. DOI: 10.1016/S0166-4115(08)62386-9. Accessed: Jul. 5, 2025.

[64] T. Heinen, M. May, and B. Schmidt, "3d visualisation in spatial data infrastructures," in *Smart Graphics*, D. Hutchison et al., Eds., vol. 3638, Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 222–229, ISBN: 978-3-540-28179-5. DOI: 10.1007/11536482_20. Accessed: Feb. 1, 2025.

[65] M. Hertzum, "Usability and user experience," in *Usability Testing*. Cham: Springer International Publishing, 2020, pp. 9–14, ISBN: 978-3-031-01099-6. DOI: 10.1007/978-3-031-02227-2_2.

[66] P. F. Hill, S. Bermudez, A. S. McAvan, J. D. Garren, M. D. Grilli, C. A. Barnes, and A. D. Ekstrom, "Age differences in spatial memory are mitigated during naturalistic navigation," *Aging, Neuropsychology, and Cognition*, vol. 31, no. 6, pp. 1106–1130, Nov. 2024, ISSN: 1382-5585, 1744-4128. DOI: 10.1080/13825585.2024.2326244. Accessed: Feb. 2, 2025.

[67] K. Höök and J. Löwgren, "Characterizing interaction design by its ideals: A discipline in transition," *She Ji: The Journal of Design, Economics, and Innovation*, vol. 7, no. 1, pp. 24–40, 2021, ISSN: 24058726. DOI: 10.1016/j.sheji.2020.12.001.

[68] B. M. Hughes, "Just noticeable differences in 2d and 3d bar charts: A psychophysical analysis of chart readability," *Perceptual and Motor Skills*, vol. 92, no. 2, pp. 495–503, Apr. 2001, ISSN: 0031-5125, 1558-688X. DOI: 10.2466/pms.2001.92.2.495.

[69] R. Hussain, S. F. A. Zaidi, A. Pedro, H. Lee, and C. Park, "Exploring construction workers' attention and awareness in diverse virtual hazard scenarios to prevent struck-by accidents," *Safety Science*, vol. 175, p. 106 526, Jul. 2024, ISSN: 09257535. DOI: 10.1016/j.ssci.2024.106526.

[70] M. I. Iglesias, M. Jenkins, and G. Morison, "An enhanced photorealistic immersive system using augmented situated visualization within virtual reality," in *2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, Lisbon, Portugal: IEEE, 2021, pp. 514–515, ISBN: 978-1-6654-4057-8. DOI: 10.1109/VRW52623.2021.00139.

[71] P. Isenberg, B. Lee, H. Qu, and M. Cordeil, "Immersive visual data stories," in *Immersive Analytics*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International Publishing, 2018, pp. 165–184, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_6. Accessed: Feb. 3, 2025.

[72] D. Isobe and Q. Yang, "An integrated finite element analysis and virtual reality system for structural and indoor nonstructural components of buildings under seismic excitations," *Journal of Building Engineering*, vol. 98, p. 111 320, Dec. 2024, ISSN: 23527102. DOI: 10.1016/j.jobe.2024.111320.

[73] E. Isomäki, T. Maijala, M. Sulkakoski, and M. Torkkel, "Dam safety guide," Kainuu Centre for Economic Development, Transport and the Environment, Technical Report 89/2012, 2012, p. 102. [Online]. Available: https://urn.fi/URN:ISBN:978-952-257-620-0.

[74] M. Janovský, P. Tobiáš, and V. Cehák, "3d visualisation of the historic pre-dam vltava river valley—procedural and cad modelling, online publishing and virtual reality," *ISPRS International Journal of Geo-Information*, vol. 11, no. 7, p. 376, 2022, ISSN: 2220-9964. DOI: 10.3390/ijgi11070376.

[75] Y. Kato and S. Watahiki, "Vibration mode identification method for structures using image correlation and compressed sensing," *Mechanical Systems and Signal Processing*, vol. 199, p. 110 495, Sep. 2023, ISSN: 08883270. DOI: 10.1016/j.ymssp.2023.110495.

[76] J. W. Kelly, T. A. Doty, S. B. Gilbert, and M. C. Dorneich, “Field of view restriction and snap turning as cybersickness mitigation tools,” *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–9, 2024, ISSN: 1077-2626, 1941-0506, 2160-9306. DOI: 10.1109/TVCG.2024.3470214.

[77] S. Khorasani, B. Victor Syiem, S. Nawaz, J. Knibbe, and E. Velloso, “Hands-on or hands-off: Deciphering the impact of interactivity on embodied learning in vr,” *Computers & Education: X Reality*, vol. 3, p. 100 037, Dec. 2023, ISSN: 29496780. DOI: 10.1016/j.cexr.2023.100037. Accessed: Feb. 3, 2025.

[78] Y. Kong and M. Guan, “Hydro-mechanical simulations aid demand-oriented design of slit dams for controlling debris flows, debris avalanches and rock avalanches,” *Engineering Geology*, vol. 326, p. 107 314, Dec. 2023, ISSN: 00137952. DOI: 10.1016/j.enggeo.2023.107314.

[79] K. Krinizki, M. S. Van Gisbergen, S. R. Rashnoodi, and T. Van Der Grinten, “A matter of perception investigating the effect of virtual reality on spatial understanding,” in *Augmented Reality and Virtual Reality*, M. C. Tom Dieck, T. H. Jung, and S. M. C. Loureiro, Eds., Cham: Springer International Publishing, 2021, pp. 277–287, ISBN: 978-3-030-68085-5. DOI: 10.1007/978-3-030-68086-2_21. Accessed: Feb. 1, 2025.

[80] V. Kronemberger, R. Cherullo, T. Azevedo, T. Porcino, and A. Raposo, “Hand gestures for continuous locomotion and snap turn for vr experiences,” in *Symposium on Virtual and Augmented Reality*, Rio Grande Brazil: ACM, Nov. 2023, pp. 243–247, ISBN: 979-8-4007-0943-2. DOI: 10.1145/3625008.3625029.

[81] C. Kuhne, E. D. Kecelioglu, S. Maltby, R. J. Hood, B. Knott, E. Ditton, F. R. Walker, and M. G. Kluge, “Direct comparison of virtual reality and 2d delivery on sense of presence, emotional and physiological outcome measures,” *Frontiers in Virtual Reality*, vol. 4, p. 1 211 001, Aug. 2023, ISSN: 2673-4192. DOI: 10.3389/frvir.2023.1211001. Accessed: Feb. 1, 2025.

[82] B. Laugwitz, T. Held, and M. Schrepp, “Construction and evaluation of a user experience questionnaire,” in *HCI and Usability for Education and Work*, A. Holzinger, Ed., vol. 5298, Berlin, Heidelberg: Springer Berlin Heidelberg, 2008, pp. 63–76, ISBN: 978-3-540-89349-3. DOI: 10.1007/978-3-540-89350-9_6. Accessed: Jul. 5, 2025.

[83] P. Leitão, "Dam health monitoring with virtual reality," M.S. thesis, Instituto Superior Técnico, 2023. [Online]. Available: https://fenix.tecnico.ulisboa.pt/cursos/meic-t/dissertacao/1128253548923665.

[84] J. Lewis and J. Sauro, "Can i leave this one out? the effect of dropping an item from the sus," *Journal of Usability Studies*, vol. 13, no. 1, pp. 38–46, 2017, ISSN: 1931-3357. [Online]. Available: https://dl.acm.org/doi/10.5555/3173069.3173073.

[85] L. Li, "Reskilling and upskilling the future-ready workforce for industry 4.0 and beyond," *Information Systems Frontiers*, Jul. 2022, ISSN: 1387-3326, 1572-9419. DOI: 10.1007/s10796-022-10308-y.

[86] K.-Y. Liang and S. L. Zeger, "Longitudinal data analysis using generalized linear models," *Biometrika*, vol. 73, no. 1, pp. 13–22, 1986, ISSN: 0006-3444, 1464-3510. DOI: 10.1093/biomet/73.1.13. Accessed: Jul. 9, 2025.

[87] R. Likert, "A technique for the measurement of attitudes," *Archives of Psychology*, vol. 140, pp. 1–55, 1932. [Online]. Available: https://psycnet.apa.org/record/1933-01885-001.

[88] S. Lin and S. Chen, "3d design of gravity dam based on virtual reality cad dynamic interactive system," *Computer-Aided Design and Applications*, vol. 19, no. S5, pp. 11–20, 2021, ISSN: 16864360. DOI: 10.14733/cadaps.2022.S5.11-20.

[89] T. Lin, R. Singh, Y. Yang, C. Nobre, J. Beyer, M. A. Smith, and H. Pfister, "Towards an understanding of situated ar visualization for basketball free-throw training," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, Yokohama Japan: ACM, 2021, pp. 1–13, ISBN: 978-1-4503-8096-6. DOI: 10.1145/3411764.3445649.

[90] W. Lin, B. Cui, D. Tong, J. Wang, X. Wang, and J. Zhang, "Development and application of three-dimensional intelligent monitoring system for rolling quality of earth-rock dam under bs framework," *Journal of Hohai University*, vol. 50, no. 5, 2022. DOI: 10.3876/j.issn.1000-1980.2022.05.018.

[91] H. Liu, D. Liu, and J. Chen, "Depth-informed point cloud-to-bim registration for construction inspection using augmented reality," *Advanced Engineering Informatics*, vol. 62, p. 102 867, Oct. 2024, ISSN: 14740346. DOI: 10.1016/j.aei.2024.102867.

[92] R. Liu, L. Wang, T. A. Koszalka, and K. Wan, "Effects of immersive virtual reality classrooms on students' academic achievement, motivation and cognitive load in science lessons," *Journal of Computer Assisted Learning*, vol. 38, no. 5, pp. 1422–1433, Oct. 2022, ISSN: 0266-4909, 1365-2729. DOI: 10.1111/jcal.12688. Accessed: Feb. 2, 2025.

[93] F. Lukowski, M. Baum, and S. Mohr, "Technology, tasks and training – evidence on the provision of employer-provided training in times of technological change in germany," *Studies in Continuing Education*, vol. 43, no. 2, pp. 174–195, May 2021, ISSN: 0158-037X, 1470-126X. DOI: 10.1080/0158037X.2020.1759525.

[94] F. Luleci, L. Li, J. Chi, D. Reiners, C. Cruz-Neira, and F. N. Catbas, "Structural health monitoring of a foot bridge in virtual reality environment," *Procedia Structural Integrity*, vol. 37, pp. 65–72, 2022, ISSN: 24523216. DOI: 10.1016/j.prostr.2022.01.060.

[95] X. Lurton, "Modelling of the sound field radiated by multibeam echosounders for acoustical impact assessment," *Applied Acoustics*, vol. 101, pp. 201–221, Jan. 2016, ISSN: 0003682X. DOI: 10.1016/j.apacoust.2015.07.012.

[96] F. Macchione, P. Costabile, C. Costanzo, and R. De Santis, "Fully-hydrodynamic modelling supporting flood hazard assessment and communication: A reference framework," *Italian Journal of Engineering Geology and Environment*, vol. 1, no. 1, pp. 101–121, 2018, ISSN: 2035-5688. DOI: 10.4408/IJEGE.2018-01.S-10.

[97] G. Makransky, S. Borre-Gude, and R. E. Mayer, "Motivational and cognitive benefits of training in immersive virtual reality based on multiple assessments," *Journal of Computer Assisted Learning*, vol. 35, no. 6, pp. 691–707, Dec. 2019, ISSN: 0266-4909, 1365-2729. DOI: 10.1111/jcal.12375. Accessed: Feb. 2, 2025.

[98] J. C. Marques, J. Rodrigues, and M. T. Restivo, "Augmented reality in groundwater flow," in *2014 11th International Conference on Remote Engineering and Virtual Instrumentation (REV)*, Porto, Portugal: IEEE, 2014, pp. 399–400, ISBN: 978-1-4799-2024-2. DOI: 10.1109/REV.2014.6784201.

[99] K. Marriott, J. Chen, M. Hlawatsch, T. Itoh, M. A. Nacenta, G. Reina, and W. Stuerzlinger, "Immersive analytics: Time to reconsider the value of 3d for information visualisation," in *Immersive Analytics*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International Publishing, 2018, pp. 25–55, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_2. Accessed: Feb. 3, 2025.

[100] A. I. Martins, A. F. Rosa, A. Queirós, A. Silva, and N. P. Rocha, "European portuguese validation of the system usability scale (sus)," *Procedia Computer Science*, vol. 67, pp. 293–300, 2015, ISSN: 18770509. DOI: 10.1016/j.procs.2015.09.273.

[101] N. C. Martins, B. Marques, S. Rafael, P. Dias, and B. S. Santos, "Seeing clearly: A situated air quality visualization with ar egocentric viewpoint extension," *Workshop on Visualisation in Environmental Sciences (EnvirVis)*, pp. 33–40, 2023. DOI: 10.2312/ENVIRVIS.20231104.

[102] N. C. Martins, "[dc] situated augmented reality: Beyond the egocentric viewpoint," in *2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, Lisbon, Portugal: IEEE, Mar. 2021, pp. 721–722, ISBN: 978-1-6654-4057-8. DOI: 10.1109/VRW52623.2021.00243.

[103] N. C. Martins, P. Dias, and B. S. Santos, "Egocentric viewpoint in mixed reality situated visualization: Challenges and opportunities," in *2020 24th International Conference Information Visualisation (IV)*, Melbourne, Australia: IEEE, Sep. 2020, pp. 9–15, ISBN: 978-1-7281-9134-8. DOI: 10.1109/IV51561.2020.00012.

[104] N. C. Martins, B. Marques, J. Alves, T. Araújo, P. Dias, and B. S. Santos, "Augmented reality situated visualization in decision-making," *Multimedia Tools and Applications*, vol. 81, no. 11, pp. 14 749–14 772, 2022, ISSN: 1380-7501, 1573-7721. DOI: 10.1007/s11042-021-10971-4.

[105] A. G. R. Marto, A. A. De Sousa, and A. J. M. Gonçalves, "Mobile augmented reality in cultural heritage context: Current technologies," in *2017 24º Encontro Português de Computação Gráfica e Interação (EPCGI)*, Guimaraes, Portugal: IEEE, Oct. 2017, pp. 1–8, ISBN: 978-1-5386-2080-9. DOI: 10.1109/EPCGI.2017.8124313.

[106] T. Mathew, "Manova in the multivariate components of variance model," *Journal of Multivariate Analysis*, vol. 29, no. 1, pp. 30–38, Apr. 1989, ISSN: 0047-259X. DOI: 10.1016/0047-259x(89)90074-2. Accessed: Jul. 8, 2025.

[107] J. W. Mauchly, "Significance test for sphericity of a normal n-variate distribution," *The Annals of Mathematical Statistics*, vol. 11, no. 2, pp. 204–209, Jun. 1940, ISSN: 0003-4851. DOI: 10.1214/aoms/1177731915. Accessed: Jul. 8, 2025.

[108] J. McCormack, J. C. Roberts, B. Bach, C. D. S. Freitas, T. Itoh, C. Hurter, and K. Marriott, "Multisensory immersive analytics," in *Immersive Analytics*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International

Publishing, 2018, pp. 57–94, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_3. Accessed: Feb. 3, 2025.

[109] O. Melnyk, M. Huymajer, D. Fenzl, C. Huemer, R. Wenighofer, and A. Mazak-Huemer, "Augmented reality for enhanced documentation and anchor inspection reporting in conventional tunnelling," *Tunnelling and Underground Space Technology*, vol. 153, p. 106 040, Nov. 2024, ISSN: 08867798. DOI: 10.1016/j.tust.2024.106040.

[110] P. Milgram and F. Kishino, "A taxonomy of mixed reality visual displays," *Institute of Electronics, Information and Communication Engineers (IEICE) Transactions on Information and Systems*, vol. E77-D, no. 12, 1994, ISSN: 0916-8532. [Online]. Available: https://search.ieice.org/bin/summary.php?id=e77-d_12_1321.

[111] C. Miller and F. Quek, "Toward multimodal situated analysis," in *Proceedings of the 13th International Conference on Multimodal Interfaces*, Alicante Spain: ACM, 2011, pp. 239–246, ISBN: 978-1-4503-0641-6. DOI: 10.1145/2070481.2070526.

[112] P. Mohammadi and C. Garrido Martins, "Cost/benefit analysis model for implementing virtual reality in construction companies," in *Construction Research Congress 2024*, Des Moines, Iowa: American Society of Civil Engineers, Mar. 2024, pp. 263–272, ISBN: 978-0-7844-8528-6. DOI: 10.1061/9780784485286.027.

[113] C. Moscoso, J. Skjermo, H. Karlsson, P. Arnesen, C.-J. Södersten, Å. S. Hoem, and G. D. Jenssen, "Analysis of spatial and design factors for users' acceptance of rescue rooms in road tunnels: An exploratory study using virtual reality," *Fire Safety Journal*, vol. 150, p. 104 272, Dec. 2024, ISSN: 03797112. DOI: 10.1016/j.firesaf.2024.104272.

[114] J. A. Nelder and R. W. M. Wedderburn, "Generalized linear models," *Journal of the Royal Statistical Society. Series A (General)*, vol. 135, no. 3, p. 370, 1972, ISSN: 0035-9238. DOI: 10.2307/2344614. JSTOR: 10.2307/2344614. Accessed: Jul. 8, 2025.

[115] V. T. Nguyen, K. Jung, and V. Gupta, "Examining data visualization pitfalls in scientific publications," *Visual Computing for Industry, Biomedicine, and Art*, vol. 4, no. 1, p. 27, Dec. 2021, ISSN: 2524-4442. DOI: 10.1186/s42492-021-00092-y. Accessed: Feb. 1, 2025.

[116] E. C. Norton, B. E. Dowd, and M. L. Maciejewski, "Odds ratios—current best practice and use," *JAMA*, vol. 320, no. 1, p. 84, Jul. 2018, ISSN: 0098-7484. DOI: 10.1001/jama.2018.6971. Accessed: Jul. 6, 2025.

[117] N. Nouri, S. Kalamkar, F. Farzinnejad, V. Biener, F. Schick, S. Kalkhof, and J. Grubert, "Improving understanding of biocide availability in facades through immersive analytics," in *2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*, Singapore, Singapore: IEEE, 2022, pp. 98–103, ISBN: 978-1-6654-5365-3. DOI: 10.1109/ISMAR-Adjunct57072.2022.00028.

[118] S. Oliveira, A. Alegre, E. Carvalho, P. Mendes, and J. Proença, "Seismic and structural health monitoring systems for large dams: Theoretical, computational and practical innovations," *Bulletin of Earthquake Engineering*, vol. 20, no. 9, pp. 4483–4512, 2022, ISSN: 1570-761X, 1573-1456. DOI: 10.1007/s10518-022-01392-1.

[119] S. Oliveira, I. Ferreira, A. Berberan, P. Mendes, J. Boavida, and B. Baptista, "Monitoring the structural integrity of large concrete dams: The case of cabril dam, portugal," in *Proceeding of Hydro 2010*, Portugal, 2010. [Online]. Available: https://www.hydropower-dams.com/product/hydro-2010-event-proceedings/.

[120] S. Oliveira and A. Silvestre, "Barragem do Cabril - Sistema para monitorização de vibrações em contínuo - Medição e análise automática da resposta dinâmica sob excitação ambiente/operacional e sob ações sísmicas," Laboratório Nacional de Engenharia Civil (LNEC), Lisbon, Portugal, Technical Report 205/2017 – DBB/NMMR, 2017, pp. 1–48. [Online]. Available: https://repositorio.lnec.pt/jspui/handle/123456789/1009599.

[121] D. Paes, J. Irizarry, and D. Pujoni, "An evidence of cognitive benefits from immersive design review: Comparing three-dimensional perception and presence between immersive and non-immersive virtual environments," *Automation in Construction*, vol. 130, p. 103 849, Oct. 2021, ISSN: 09265805. DOI: 10.1016/j.autcon.2021.103849. Accessed: Feb. 1, 2025.

[122] W. Pan, "Akaike's information criterion in generalized estimating equations," *Biometrics*, vol. 57, no. 1, pp. 120–125, Mar. 2001, ISSN: 0006-341X, 1541-0420. DOI: 10.1111/j.0006-341x.2001.00120.x. Accessed: Jul. 9, 2025.

[123] T. Pinto, "Simulation of dam failures in vr," M.S. thesis, Instituto Superior Técnico, University of Lisbon, Lisbon, Portugal, 2024. [Online]. Available: https://fenix.tecnico.ulisboa.pt/cursos/merc/dissertacao/3098578385895598.

[124] L. Pöhler and F. Teuteberg, "Suitability- and utilization-based cost–benefit analysis: A techno-economic feasibility study of virtual reality for workplace and process

design," *Information Systems and e-Business Management*, Nov. 2023, ISSN: 1617-9846, 1617-9854. DOI: 10.1007/s10257-023-00658-8.

[125] E. A. Portela and J. Bento, "Dam safety: Improving management," in *Artificial Intelligence in Structural Engineering*, J. G. Carbonell, J. Siekmann, G. Goos, J. Hartmanis, J. Van Leeuwen, and I. Smith, Eds., vol. 1454, Berlin, Heidelberg: Springer Berlin Heidelberg, 1998, pp. 455–458, ISBN: 978-3-540-64806-2. DOI: 10.1007/BFb0030473.

[126] B. Preim and R. Dachselt, "User Interface Engineering," in *Interaktive Systeme: Band 2: User Interface Engineering, 3D-Interaktion, Natural User Interfaces*, ser. eXamen.press, Berlin, Heidelberg: Springer Berlin Heidelberg, 2015, ISBN: 978-3-642-45246-8. DOI: 10.1007/978-3-642-45247-5.

[127] F. Ramos, O. Ripolles, and M. Chover, "Continuous level of detail for large scale rendering of 3d animated polygonal models," in *Articulated Motion and Deformable Objects*, D. Hutchison et al., Eds., vol. 7378, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 194–203, ISBN: 978-3-642-31566-4. DOI: 10.1007/978-3-642-31567-1_19.

[128] C. R. Rao, "Generalisation of markoff's theorem and tests of linear hypotheses," *Sankhyā: The Indian Journal of Statistics (1933-1960)*, vol. 7, no. 1, pp. 9–16, 1945, ISSN: 00364452. JSTOR: 25047825. Accessed: Jul. 8, 2025. [Online]. Available: http://www.jstor.org/stable/25047825.

[129] M. Rashidi and S. M. Haeri, "Evaluation of behaviors of earth and rockfill dams during construction and initial impounding using instrumentation data and numerical modeling," *Journal of Rock Mechanics and Geotechnical Engineering*, vol. 9, no. 4, pp. 709–725, Aug. 2017, ISSN: 16747755. DOI: 10.1016/j.jrmge.2016.12.003.

[130] R. Raskar, G. Welch, and Wei-Chao Chen, "Table-top spatially-augmented realty: Bringing physical models to life with projected imagery," in *Proceedings 2nd IEEE and ACM International Workshop on Augmented Reality (IWAR'99)*, San Francisco, CA, USA: IEEE Comput. Soc, 1999, pp. 64–71, ISBN: 978-0-7695-0359-2. DOI: 10.1109/IWAR.1999.803807. Accessed: Feb. 9, 2025.

[131] M. Ready, T. Dwyer, and J. Haga, "Immersive visualization of big data for river disaster management," in *Proceedings of the IEEE VIS - Workshop on Immersive Analytics: Exploring Future Interaction and Visualization Technologies for Data*

Analytics, Phoenix, USA: IEEE, 2017, pp. 1–4. [Online]. Available: https://groups.inf.ed.ac.uk/vishub/immersiveanalytics/papers/IA_1538-paper.pdf.

[132] I. Rehamnia, B. Benlaoukli, M. Jamei, M. Karbasi, and A. Malik, "Simulation of seepage flow through embankment dam by using a novel extended kalman filter based neural network paradigm: Case study of fontaine gazelles dam, algeria," *Measurement*, vol. 176, p. 109 219, 2021, ISSN: 02632241. DOI: 10.1016/j.measurement.2021.109219.

[133] B. Ren, X. Lu, X. Wang, D. Wang, J. Wang, and J. Yu, "Mobile augmented reality visualization of high arch dam construction simulations based on simultaneous localization and mapping optimization," *Journal of Hydroelectric Engineering*, vol. 40, no. 11, pp. 115–128, 2021. DOI: 10.11660/slfdxb.20211111.

[134] T. Rhyne, M. Tory, T. Munzner, M. Ward, C. Johnson, and D. Laidlaw, "Information and scientific visualization: Separate but equal or happy together at last," in *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, Seattle, WA, USA: IEEE, 2003, pp. 611–614, ISBN: 978-0-7803-8120-9. DOI: 10.1109/VISUAL.2003.1250428. Accessed: Feb. 1, 2025.

[135] N. Rogeau and A. Rezaei Rad, "Collaborative timber joint assembly: Augmented reality for multi-level human-robot interaction," *International Journal of Architectural Computing*, vol. 22, no. 4, pp. 642–660, Dec. 2024, ISSN: 1478-0771, 2048-3988. DOI: 10.1177/14780771241286605.

[136] A. F. Rosa, A. I. Martins, V. Costa, A. Queiros, A. Silva, and N. P. Rocha, "European portuguese validation of the post-study system usability questionnaire (pssuq)," in *2015 10th Iberian Conference on Information Systems and Technologies (CISTI)*, Aveiro, Portugal: IEEE, Jun. 2015, pp. 1–5, ISBN: 978-989-98434-5-5. DOI: 10.1109/CISTI.2015.7170431. Accessed: Jul. 5, 2025.

[137] R. Rosenthal, *Meta-Analytic Procedures for Social Research*. 2455 Teller Road, Thousand Oaks California 91320 United States of America: SAGE Publications, Inc., 1991, ISBN: 978-0-8039-4246-2. DOI: 10.4135/9781412984997. Accessed: Jul. 6, 2025.

[138] K. A. Satriadi, A. Cunningham, R. T. Smith, T. Dwyer, A. Drogemuller, and B. H. Thomas, "Proxsituated visualization: An extended model of situated visualization using proxies for physical referents," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, Hamburg Germany: ACM, 2023, pp. 1–20, ISBN: 978-1-4503-9421-5. DOI: 10.1145/3544548.3580952.

[139] K. A. Satriadi, B. Ens, S. Goodwin, and T. Dwyer, "Active proxy dashboard: Binding physical referents and abstract data representations in situated visualization through tangible interaction," in *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, Hamburg Germany: ACM, Apr. 2023, pp. 1–7, ISBN: 978-1-4503-9422-2. DOI: 10.1145/3544549.3585797.

[140] Y. Sauer, A. Sipatchin, S. Wahl, and M. García García, "Assessment of consumer vr-headsets' objective and subjective field of view (fov) and its feasibility for visual field testing," *Virtual Reality*, vol. 26, no. 3, pp. 1089–1101, Sep. 2022, ISSN: 1359-4338, 1434-9957. DOI: 10.1007/s10055-021-00619-x. Accessed: Feb. 8, 2025.

[141] S. Seipel and L. Carvalho, "Solving combined geospatial tasks using 2d and 3d bar charts," in *2012 16th International Conference on Information Visualisation*, Montpellier, France: IEEE, Jul. 2012, pp. 157–163, ISBN: 978-1-4673-2260-7. DOI: 10.1109/IV.2012.36. Accessed: Feb. 1, 2025.

[142] S. Senanayake, P. A. M. Gunawardana, B. Perera, and D. Rajaratnam, "Examining the potential use of augmented reality in construction cost management tools and techniques," *Journal of Engineering, Design and Technology*, Jan. 2023, ISSN: 1726-0531, 1726-0531. DOI: 10.1108/JEDT-10-2022-0512.

[143] S. Seo, H. Park, and C. Koo, "Impact of interactive learning elements on personal learning performance in immersive virtual reality for construction safety training," *Expert Systems with Applications*, vol. 251, p. 124 099, Oct. 2024, ISSN: 09574174. DOI: 10.1016/j.eswa.2024.124099.

[144] T. Sequeira, "Immersive analytics for dam analysis," M.S. thesis, Instituto Superior Técnico, University of Lisbon, Lisbon, Portugal, 2023. [Online]. Available: https://fenix.tecnico.ulisboa.pt/cursos/meic-a/dissertacao/1972678479055752.

[145] S. S. Shapiro and M. B. Wilk, "An analysis of variance test for normality (complete samples)," *Biometrika*, vol. 52, no. 3-4, pp. 591–611, Dec. 1965, ISSN: 0006-3444, 1464-3510. DOI: 10.1093/biomet/52.3-4.591. Accessed: Jul. 7, 2025.

[146] S. Shewchuk, J. Wallace, and M. Seibold, "Evaluations of training programs to improve capacity in k*: A systematic scoping review of methods applied and outcomes assessed," *Humanities and Social Sciences Communications*, vol. 10, no. 1, p. 887, Nov. 2023, ISSN: 2662-9992. DOI: 10.1057/s41599-023-02403-5.

[147] S. Shin, A. Batch, P. W. S. Butcher, P. D. Ritsos, and N. Elmqvist, "The reality of the situation: A survey of situated analytics," *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–19, 2023, ISSN: 1077-2626, 1941-0506, 2160-9306. DOI: 10.1109/TVCG.2023.3285546.

[148] R. Skarbez, N. F. Polys, J. T. Ogle, C. North, and D. A. Bowman, "Immersive analytics: Theory and research agenda," *Frontiers in Robotics and AI*, vol. 6, p. 82, 2019, ISSN: 2296-9144. DOI: 10.3389/frobt.2019.00082.

[149] T. Soares, "Immersive exploration of dam galleries," M.S. thesis, Instituto Superior Técnico, University of Lisbon, Lisbon, Portugal, 2024. [Online]. Available: https://fenix.tecnico.ulisboa.pt/cursos/merc/dissertacao/3098578385895509.

[150] M. P. D. Souza and M. M. Fabricio, "Bim and virtual reality for pre-design evaluation of building performance," *Architectural Engineering and Design Management*, vol. 20, no. 5, pp. 1260–1279, Sep. 2024, ISSN: 1745-2007, 1752-7589. DOI: 10.1080/17452007.2024.2388714.

[151] H. R. Spero, I. Vazquez-Lopez, K. Miller, R. Joshaghani, S. Cutchin, and J. Enterkine, "Drones, virtual reality, and modeling: Communicating catastrophic dam failure," *International Journal of Digital Earth*, vol. 15, no. 1, pp. 585–605, 2022, ISSN: 1753-8947, 1753-8955. DOI: 10.1080/17538947.2022.2041116.

[152] W. Stuerzlinger, T. Dwyer, S. Drucker, C. Görg, C. North, and G. Scheuermann, "Immersive human-centered computational analytics," in *Immersive Analytics*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International Publishing, 2018, pp. 139–163, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_5. Accessed: Feb. 3, 2025.

[153] Y. Tan, W. Xu, P. Chen, and S. Zhang, "Building defect inspection and data management using computer vision, augmented reality, and bim technology," *Automation in Construction*, vol. 160, p. 105 318, Apr. 2024, ISSN: 09265805. DOI: 10.1016/j.autcon.2024.105318.

[154] B. H. Thomas et al., "Situated analytics," in *Immersive Analytics*, K. Marriott, F. Schreiber, T. Dwyer, K. Klein, N. H. Riche, T. Itoh, W. Stuerzlinger, and B. H. Thomas, Eds., vol. 11190, Cham: Springer International Publishing, 2018, pp. 185–220, ISBN: 978-3-030-01387-5. DOI: 10.1007/978-3-030-01388-2_7.

[155] T. S. Tullis and J. N. Stetson, "A comparison of questionnaires for assessing website usability," in *Proceedings of the Usability Professionals Association (UPA) 2004 Conference*, Usability Professionals Association (UPA), 2004, pp. 7–11. [Online]. Available: https://api.semanticscholar.org/CorpusID:9670323.

[156] J. M. Valderrama-Zafra, P. Fernández-Rodríguez, A. Oya, R. Carrasco, M. A. Rubio-Paramio, M. S. Garrido-Carretero, and C. Azorit, "Assessing 3d vs. 2d habitat metrics in a mediterranean ecosystem for a wiser wildlife management," *Ecological Informatics*, vol. 69, p. 101 623, Jul. 2022, ISSN: 15749541. DOI: 10.1016/j.ecoinf.2022.101623. Accessed: Feb. 1, 2025.

[157] N. Verdelho Trindade, "Augmented reality in dam monitoring," MSc Thesis, University of Lisbon, Lisbon, Portugal, 2018. [Online]. Available: https://fenix.tecnico.ulisboa.pt/downloadFile/844820067126014/Thesis.pdf.

[158] N. Verdelho Trindade, Ó. Amaro, D. Brás, D. Gonçalves, and J. Madeiras Pereira, "Visualizing plasma physics simulations in immersive environments," in *Proceedings of the 19th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - IVAPP*, Rome, Italy: SciTePress, 2024, pp. 645–652, ISBN: 978-989-758-679-8. DOI: 10.5220/0012357100003660.

[159] N. Verdelho Trindade, L. Custódio, A. Ferreira, and J. M. Pereira, "Improving ray tracing understanding with immersive environments," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1975–1988, 2024, ISSN: 1939-1382, 2372-0050. DOI: 10.1109/TLT.2024.3436656.

[160] N. Verdelho Trindade, A. Ferreira, D. Gonçalves, and S. Oliveira, "The future of structural health monitoring with extended reality (chapter 30)," in *Digital Transformation in the Construction Industry*, ser. Woodhead Publishing Series in Civil and Structural Engineering, 1st ed., S.l.: Woodhead Publishing, 2025, pp. 593–620, ISBN: 978-0-443-29861-5. [Online]. Available: https://doi.org/10.1016/B978-0-443-29861-5.00030-5.

[161] N. Verdelho Trindade, A. Ferreira, J. Madeiras Pereira, and S. Oliveira, "Extended reality in aec," *Automation in Construction*, vol. 154, p. 105 018, Oct. 2023, ISSN: 09265805. DOI: 10.1016/j.autcon.2023.105018.

[162] N. Verdelho Trindade, A. Ferreira, and S. Oliveira, "Damar: Augmented reality in dam safety control," *International Journal on Hydropower and Dams*, vol. 26, no. 5, p. 7, 2019. [Online]. Available: https://www.hydropower-dams.com/articles/damar-augmented-reality-in-dam-safety-control/.

[163] N. Verdelho Trindade, A. Ferreira, and S. Oliveira, “Extended reality in the safety control of dams,” in *Fourth International Dam World Conference - DW2020. Vol. 1, Paper 169, Pag. 71-89, 20 Pages*, vol. 1, Lisbon, Portugal: Laboratório Nacional de Engenharia Civil (LNEC), 2020, pp. 71–89. [Online]. Available: https://repositorio.lnec.pt/jspui/handle/123456789/1012969.

[164] N. Verdelho Trindade, P. Leitão, D. Gonçalves, S. Oliveira, and A. Ferreira, “Immersive Situated Analysis of Dams’ Behavior,” in *Conference Proceedings of the Fifth International Conference on Graphics and Interaction - ICGI 2023*, Tomar, Portugal: Eurographics, IEEE, 2023, pp. 105–112, ISBN: 979-8-3503-5818-6. DOI: 10.1109/ICGI60907.2023.10452725.

[165] N. Verdelho Trindade, P. Leitão, D. Gonçalves, S. Oliveira, and A. Ferreira, “The role of situatedness in immersive dam visualization: Comparing proxied with immediate approaches,” *Computers*, vol. 13, no. 2, p. 35, Jan. 2024, ISSN: 2073-431X. DOI: 10.3390/computers13020035.

[166] S. Verdugo-Castro, A. García-Holgado, and M. C. Sánchez-Gómez, “The gender gap in higher stem studies: A systematic literature review,” *Heliyon*, vol. 8, no. 8, e10300, Aug. 2022, ISSN: 24058440. DOI: 10.1016/j.heliyon.2022.e10300.

[167] S. Verdugo-Castro, M. C. Sánchez-Gómez, and A. García-Holgado, “Factors associated with the gender gap in the stem sector: Comparison of theoretical and empirical concept maps and qualitative swot analysis,” *Heliyon*, vol. 9, no. 6, e17499, Jun. 2023, ISSN: 24058440. DOI: 10.1016/j.heliyon.2023.e17499.

[168] A. Wald, “Tests of statistical hypotheses concerning several parameters when the number of observations is large,” *Transactions of the American Mathematical Society*, vol. 54, no. 3, p. 426, Nov. 1943, ISSN: 0002-9947. DOI: 10.2307/1990256. JSTOR: 1990256. Accessed: Jul. 9, 2025.

[169] D. Wang, X. Wang, B. Ren, J. Wang, T. Zeng, D. Kang, and G. Wang, “Vision-based productivity analysis of cable crane transportation using augmented reality–based synthetic image,” *Journal of Computing in Civil Engineering*, vol. 36, no. 1, p. 04 021 030, 2022, ISSN: 0887-3801, 1943-5487. DOI: 10.1061/(ASCE)CP.1943-5487.0000994.

[170] K.-C. Wang, S.-H. Wang, C.-J. Kung, S.-W. Weng, and W.-C. Wang, “Applying bim and visualization techniques to support construction quality management for soil and water conservation construction projects,” in *34th International Symposium*

on Automation and Robotics in Construction, Taipei, Taiwan, 2018. DOI: 10.22260/ISARC2018/0099.

[171] W. Wang, X. Li, and Z. Deng, “The development and application of 3-d visual display platform for safety monitoring information of hydropower project,” *IOP Conference Series: Earth and Environmental Science*, vol. 189, p. 022 050, 2018, ISSN: 1755-1315. DOI: 10.1088/1755-1315/189/2/022050.

[172] 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*, Sydney NSW Australia: ACM, Oct. 2023, pp. 1–12, ISBN: 979-8-4007-0281-5. DOI: 10.1145/3607822.3614542.

[173] Z. Wen, W. Zeng, L. Weng, Y. Liu, M. Xu, and W. Chen, “Effects of view layout on situated analytics for multiple-view representations in immersive visualization,” *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–11, 2022, ISSN: 1077-2626, 1941-0506, 2160-9306. DOI: 10.1109/TVCG.2022.3209475.

[174] N. Wenk, J. Penalver-Andres, K. A. Buetler, T. Nef, R. M. Müri, and L. Marchal-Crespo, “Effect of immersive visualization technologies on cognitive load, motivation, usability, and embodiment,” *Virtual Reality*, vol. 27, no. 1, pp. 307–331, Mar. 2023, ISSN: 1359-4338, 1434-9957. DOI: 10.1007/s10055-021-00565-8. Accessed: Feb. 1, 2025.

[175] S. White, S. Feiner, and J. Kopylec, “Virtual vouchers: Prototyping a mobile augmented reality user interface for botanical species identification,” in *3D User Interfaces (3DUI’06)*, Alexandria, VA, USA: IEEE, 2006, pp. 119–126, ISBN: 978-1-4244-0225-0. DOI: 10.1109/VR.2006.145.

[176] S. White and S. Feiner, “Sitelens: Situated visualization techniques for urban site visits,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Boston MA USA: ACM, 2009, pp. 1117–1120, ISBN: 978-1-60558-246-7. DOI: 10.1145/1518701.1518871.

[177] F. Wilcoxon, “Individual comparisons by ranking methods,” *Biometrics Bulletin*, vol. 1, no. 6, p. 80, Dec. 1945, ISSN: 0099-4987. DOI: 10.2307/3001968. JSTOR: 10.2307/3001968. Accessed: Jul. 7, 2025.

[178] W. Willett, Y. Jansen, and P. Dragicevic, “Embedded data representations,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 461–470, 2017, ISSN: 1077-2626. DOI: 10.1109/TVCG.2016.2598608.

[179] World Bank, *World bank open data - population, total*, 2023. Accessed: May 1, 2023. [Online]. Available: https://data.worldbank.org/indicator/SP.POP.TOTL.

[180] World Bank, *World bank open data - researchers in r&d (per million people)*, 2023. Accessed: May 1, 2023. [Online]. Available: https://data.worldbank.org/indicator/SP.POP.SCIE.RD.P6.

[181] M. H. Yimam, "Impact of training on employees performance: A case study of bahir dar university, ethiopia," *Cogent Education*, vol. 9, no. 1, p. 2 107 301, Dec. 2022, ISSN: 2331-186X. DOI: 10.1080/2331186X.2022.2107301.

[182] M. Ze and D. Yu, "Space renovation in virtual reality," in *Designing Interactive Systems Conference*, IT University of Copenhagen Denmark: ACM, Jul. 2024, pp. 130–134, ISBN: 979-8-4007-0632-5. DOI: 10.1145/3656156.3663711.

[183] Y. Zhang, B. Ens, K. A. Satriadi, Y. Yang, and S. Goodwin, "Defining embodied provenance for immersive sensemaking," in *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, Hamburg Germany: ACM, Apr. 2023, pp. 1–7, ISBN: 978-1-4503-9422-2. DOI: 10.1145/3544549.3585691. Accessed: Feb. 9, 2025.

[184] J. Zhao and J. Zhang, "Application of multimedia technology in water conservancy and hydropower engineering," *Journal of Visual Communication and Image Representation*, vol. 71, p. 102 707, 2020, ISSN: 10473203. DOI: 10.1016/j.jvcir.2019.102707.

[185] M. Zhao, Y. Su, J. Zhao, S. Chen, and H. Qu, "Mobile situated analytics of ego-centric network data," in *SIGGRAPH Asia 2017 Symposium on Visualization*, Bangkok Thailand: ACM, 2017, pp. 1–8, ISBN: 978-1-4503-5411-0. DOI: 10.1145/3139295.3139309.

[186] M. Zheng and A. G. Campbell, "Location-based augmented reality in-situ visualization applied for agricultural fieldwork navigation," in *2019 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)*, Beijing, China: IEEE, 2019, pp. 93–97, ISBN: 978-1-7281-4765-9. DOI: 10.1109/ISMAR-Adjunct.2019.00039.

[187] D. Zhong, Z. Wang, T. Guan, D. Wang, and Y. Yan, "Visual simulation of construction schedule for core rock-fill dam based on augmented reality," *Journal of Tianjin University Science and Technology*, vol. 51, no. 10, pp. 1072–1085, 2018. DOI: http://dx.doi.org/10.11784/tdxbz201710028.