ARTIV BCI: AUGMENTED REALITY + TABLET INTERFACE FOR VISUALIZING BRAIN COMPUTER INTERFACE DATA

by

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Dedicated to my family and friends

Contents

List of Tables . . . . **viii**

List of Figures . . . . **ix**

Abstract . . . . **xiii**

List of Abbreviations and Symbols . . . . **xiv**

Acknowledgements . . . . **xvi**

Chapter 1 Introduction **1**

Chapter 2 Research background **7**

2.1 Augmented reality 7

2.2 Limitations of conventional displays 8

2.3 Brain computer interface 10

2.4 Time series analysis in EEG 12

2.5 Valence and arousal 12

2.6 Feature extraction and data visualization in brain computer interface 14

2.7 Frequency composition, windowing and ERP signatures in BCI 14

2.8 BCI with augmented reality and other applications 15

2.9 BrainZebo - A neurofeedback project 16

2.10 Physical displays 17

2.11 Hybrid interfaces 18

2.12 Extended physical displays using augmented reality - Relevant works and challenges 19

2.13 Data visualization in extended displays 20

2.14 Spatial alignment of AR displays 21

2.15 Immersive analytics 22

2.16 Existing tools and platforms to visualize BCI data 23

2.17 Design choices 24
2.17.1 Why BCI data? 26
2.17.2 Resting position 26

2.18 Summary of background work 26

Chapter 3 System overview 28

3.1 Overview of AbVD and ArVD in ARTIV-BCI 28

3.2 Design 30
3.2.1 Initial brainstorming 30
3.2.2 UI sketching 30
3.2.3 Low-fidelity prototype 30
3.2.4 High-fidelity prototype 34
3.2.5 Design Testing and Feedback 34

3.3 Implementation 35
3.3.1 BCI data collection using OpenVibe 35
3.3.2 Visualizing BCI data on the tablet and HoloLens 2 using D3 js 38
3.3.3 Communication between the tablet and HoloLens 2 applications 38
3.3.4 Aligning AR content with the tablet 38
3.3.5 Transparency in AR layers 38
3.3.6 Deploying HoloLens application 39
3.3.7 AbVD 39
3.3.8 ArVD 42
3.3.9 Summary of implementation 44

Chapter 4 Comparative Evaluation of AbVD and ArVD vs. Tablet-Only Interfaces 45

4.1 Research questions 45
4.1.1 AbVD 45
4.1.2 ArVD 46

4.2 Study overview 47
4.2.1 Study notice 48
4.2.2 Initial screening of participants 49
4.2.3 Consent and briefing 49
4.2.4 Software tools and devices used 50
4.2.5 Setting up the study room 50
4.2.6 BCI introduction video 50

4.3 Experiments 51

4.3.1 Counterbalancing of experiments 51
4.3.2 Experiment 1: AbVD 52
4.3.3 Experiment 2: Around Display 54

4.4 Preparing the data for data analysis 55
4.4.1 Data collection 55
4.4.2 Preparing the data 57

Chapter 5 Data Analysis and Results 76

5.1 Study population 76

5.2 Statistical data analysis results for AbVD 76
5.2.1 Accuracy - Testing hypothesis HA1 76
5.2.2 Time-taken - Testing hypothesis for HA2 81
5.2.3 Custom questionnaire analysis for AbVD 83
5.2.4 NASA TLX 83
5.2.5 System Usability Scores(SUS) 87

5.3 Behaviour analysis for AbVD 89
5.3.1 Video observations 89
5.3.2 Think-aloud 94

5.4 Qualitative data analysis AbVD - interviews 95
5.4.1 Visual distinction of data in AR 95
5.4.2 Advantages of AR layers 95
5.4.3 Toggle feature and number of layers 96

5.5 Summary of Data Analysis - AbVD 96

5.6 Statistical data analysis results for Around display (ArVD) 97
5.6.1 Accuracy - Testing hypothesis HB1 97
5.6.2 Time taken- Testing hypothesis HB2 99
5.6.3 Custom questionnaire analysis ArVD 100
5.6.4 NASA TLX 103
5.6.5 System usability score 103

5.7 Behaviour analysis for ArVD 106
5.7.1 Video observations 106
5.7.2 Think-aloud 108

5.8 Qualitative data analysis - ArVD interviews 109
5.8.1 Impact of focus+context view in terms of data comprehension in BCI 109
5.8.2 ArVD required limited interaction 109

5.9 Summary of Data Analysis - ArVD 109

5.10 Thematic analysis results from semi-structured interviews 112
5.10.1 User experience 112
5.10.2 Implementation 113
5.10.3 Future applications 115

5.11 Review of findings in relation to the research questions 115
5.11.1 Above display 116
5.11.2 Around display 117

Chapter 6 Discussion 119

6.0.1 Lessons learnt from our research 119
6.0.2 Contributions and related works 127
6.0.3 Summary of Limitations 129
6.0.4 Future work 131

Chapter 7 Conclusion 133

Bibliography 134

Appendix A Recruitment notice to students 149

Appendix B Consent form for the participants 150

Appendix C Task list for Above display and Around display 153

Appendix D Questionnaire for Hololens familiarity and Participant background 164

Appendix E Above display - Interface and post condition questionnaire 167

Appendix F Around display - Interface and post condition questionnaire 176

Appendix G System Usability Scale(SUS) 187

Appendix H Task Load Index(NASA-TLX) 189

Appendix I Debriefing and interview 191

Appendix J **Checklist for study** **192**

Appendix K **Participants diversity** **193**

List of Tables

4.1 Estimated time for each task in the study 53

4.2 Data from custom questionnaire spreadsheet (SA - Strongly agree, A- Agree, N - Neutral, D - Disagree, SD - Strongly disagree) . . 58

4.3 Data from NASA TLX spreadsheet 60

4.4 SUS calculation spreadsheet 61

4.5 IRR calculation 73

4.6 IRR codebook 75

5.1 Average time taken for each tasks in above display 77

5.2 AbVD Statistical analysis results on custom questionnaire responses 86

5.3 NASA TLX - Perceived task load summary for AbVD 89

5.4 AbVD - Summary of data analysis 96

5.5 Average time taken for each tasks in around display 97

5.6 ArVD - Statistical analysis results on custom questionnaire responses 110

5.7 NASA TLX - Perceived task load summary for ArVD 111

5.8 ArVD - Summary of data analysis 111

List of Figures

3.1	Overview of AbVD	29
3.2	Overview of ArVD	29
3.3	Brainstorming using Miro board	31
3.4	UI Sketching	32
3.5	Low-fidelity prototype	33
3.6	High-fidelity prototype	34
3.7	Signal processing architecture in openVibe to capture alpha, beta frequencies of F3 and F4, valence and arousal values	37
3.8	QR code attached to the tablet to align the AR contents	39
3.9	Menu for above and around display with QR tracking	40
3.10	AbVD interface	41
3.11	ArVD interface	43
4.1	Recruitment, consent and pre-screening process	48
4.2	AbVD and ArVD Experiments	49
4.3	Study venue	51
4.4	Counterbalancing of experiments	52
4.5	Tablet only interface for comparison with AbVD	54
4.6	Tablet only interface for comparison with ArVD	56
4.7	Codebook	62
4.8	Affinity diagram - user experience (Layering advantages)	63
4.9	Affinity diagram - user experience (Visual distinction and big picture view in AR)	64
4.10	Affinity diagram - user experience (Physical constraints and engaging experience)	65
4.11	Affinity diagram - user experience (Layering advantages)	66

4.12	Affinity diagram - implementation (Number of layers)	67
4.13	Affinity diagram - implementation (Resolution)	68
4.14	Affinity diagram - implementation (Toggle and color blending)	69
4.15	Affinity diagram - implementation (Grid and hybrid interface)	70
4.16	Affinity diagram - future applications (Generic applications)	71
4.17	Affinity diagram - future applications (Live data)	72
4.18	Interaction logs from tablet	74
5.1	Accuracy for seated and toggle tasks	78
5.2	Accuracy for view from an angle tasks	79
5.3	Accuracy for Stand up and look down tasks	80
5.4	Accuracy for use your approach tasks	80
5.5	Time taken for seated and toggle tasks	81
5.6	Time taken for view from an angle tasks	82
5.7	Time taken for stand up and look down tasks	82
5.8	Time taken for use your own approach tasks	83
5.9	AbVD custom questionnaire	84
5.10	AbVD custom questionnaire (Continued)	85
5.11	AbVD NASA-TLX	87
5.12	AbVD - Comparison of TLX factors	88
5.13	System usability scores comparison	90
5.14	Accuracy of focus+context tasks	98
5.15	Accuracy your use own approach tasks	99
5.16	Time taken for focus+context tasks	100
5.17	Time taken for use your approach tasks	100
5.18	ArVD custom questionnaire	101
5.19	ArVD custom questionnaire (Continued)	102
5.20	ArVD NASA-TLX	104

5.21 ArVD - Comparison of TLX factors 105
5.22 System usability score comparison 106

6.1 Above display - Time taken and Accuracy 121
6.2 Around display - Time taken and Accuracy 121

A.1 Recruitment notice to students 149

B.1 Consent form 150
B.2 Consent form(Cont) 151
B.3 Consent form(Cont) 152

C.1 Training tasks for Above display and physical monitors 153
C.2 Task-set 1 Above display 154
C.3 Task-set 1 Above display Cont. 155
C.4 Task-set 2 Above display 156
C.5 Task-set 2 Above display Cont. 157
C.6 Training tasks for Around display and physical monitors . . . 158
C.7 Training tasks for Around display and physical monitors Cont. 159
C.8 Task-set 1 Around display 160
C.9 Task-set 1 Around display Cont. 161
C.10 Task-set 2 Around display 162
C.11 Task-set 2 Around display Cont. 163

D.1 Hololens familiarity questionnaire 164
D.2 Participant background questionnaire 165
D.3 Participant background questionnaire cont 166

E.1 Above display 167
E.2 Above display cont. 168
E.3 Above display cont. 169

E.4 Above display - Physical monitors cont. 170
E.5 Above display - Physical monitors cont. 171
E.6 Above display - Physical monitors cont. 172
E.7 Above display - Post condition questionnaire 173
E.8 Above display - Post condition questionnaire cont. 174
E.9 Above display - Post condition questionnaire cont. 175

F.1 Around display - Interface questionnaire 176
F.2 Around display - Interface questionnaire cont. 177
F.3 Around display - Interface questionnaire cont. 178
F.4 Around display - Interface questionnaire cont. 179
F.5 Around display Physical monitors - Interface questionnaire . . 180
F.6 Around display Physical monitors - Interface questionnaire cont. 181
F.7 Around display Physical monitors - Interface questionnaire cont. 182
F.8 Around display Physical monitors - Interface questionnaire cont. 183
F.9 Around display - Post condition questionnaire 184
F.10 Around display - Post condition questionnaire cont. 185
F.11 Around display - Post condition questionnaire cont. 186

G.1 System usability questionnaire 187
G.2 System usability questionnaire cont. 188

H.1 NASA-TLX questionnaire 189
H.2 NASA-TLX questionnaire cont. 190

I.1 Debriefing and interview 191

J.1 Study checklist 192

K.1 Participants diversity 193

Abstract

Over-plotting and screen size are issues that challenge multivariate data visualization, even on large displays. Large datasets make scrolling through data tedious, and pose difficulties in isolating data points. Multivariate datasets can require displaying multiple graphs, which incurs cognitive load for the user when context switching between graphs. A hybrid tablet + augmented reality(AR) interface can visualize large data in AR beyond the boundaries of the conventional screen, which may permit effective multivariate data visualization. In this research I designed and evaluated a hybrid tablet and head-worn AR interface to visualize multivariate Brain-Computer Interface(BCI) time-series data. I explored two techniques for combining a head-worn AR display with a tablet display for information visualization: rendering 2D AR content in layers above the tablet display, and rendering 2D AR content around and on the same visual plane as the tablet display. I conducted a controlled within-subjects experiment to comparatively evaluate the above display and around display AR interfaces against a tablet-only interface. In the above-display experiment, multivariate time-series data is presented in four AR layers above the display. In the around-display experiment a long duration time series extends beyond the edges of the display. I collected task accuracy and time to complete tasks as primary measures. Semi-structured interviews, self-reported usability and task load scores, and custom questionnaire responses are collected for interface feedback. Above display AR yielded significantly higher task accuracy but more time taken for task completion than the tablet only interface when looking through the four horizontal AR layers in a standing position. Around display AR yielded significantly higher task accuracy than the tablet only interface and similar time taken to complete tasks. Still, participants expressed numerous reservations about the hybrid setup, including higher task load and lower perceived usability vs. the tablet only configuration.

List of Abbreviations and Symbols

AR: Augmented Reality

HMD: Head-Mounted Display

BCI: Brain-Computer Interface

Tablet+AR: Tablet+Augmented Reality

AbVD: Above display/Above visualization of data

ArVD: Around display/Around visualization of data

QR: Quick Response code

MR: Mixed Reality

NASA-TLX: NASA Task Load Index

SUS: System Usability Score

VR: Virtual Reality

XR: Mixed-reality

SVM: Support Vector Machine

UMP: Universal Windows Platform

UI User Interface

ms: Milliseconds

Mdn: Sample median

F: F-statistic

W: SPSS-statistic

df: Degree of freedom

p: Probability of Type I Error

M: Sample mean

SD: Standard deviation

α_{new}: Alpha level

ϵ^2: Epsilon squared

r: r-statistic

χ^2: Chi-squared

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Chapter 1

Introduction

For visualizing longer duration and multivariate time series data, conventional displays such as tablets, personal computers and large interactive displays have limitations due to screen size, portability and over-plotting [48]. For visualizing such data, a hybrid interface that combines conventional display and augmented reality can be leveraged. In such displays, a user can perceive large amounts of data without such limitations. In our research, we designed tablet + AR with layering and focus+context techniques to address data congestion due to screen size. We implemented layering and focus+context techniques in two separate interfaces called above display visualization of data **(AbVD)** and around display visualization of data **(ArVD)**. In AbVD interface, AR content is presented in four horizontal layers above the tablet display. In ArVD, the AR content extends the visualization on the tablet from close to the edges of the display.

There are different types of displays for presenting data such as laptops, tablets and phones, split screen displays, large screen displays and curved screen displays; though not all displays is suitable for every type of data presentation. These conventional displays with limited screen size could impact certain types of data visualization [1] such as poor visibility or interpretation of plots when sub-trends are overlapped. Such limitations cannot be overcome using larger screens due to portability [4]. The benefits of focus+context and overview+detail displays in AR proved to be effective to support data visualization and overcome the difficulty of screen size. Also, AR can extend the data visualization by presenting additional content of the visualization beyond the physical screens [1].

In earlier research, data visualization using Tablet and augmented reality is demonstrated by Langner et al.[1] and Reipschläger et al. [3]. MARVIS [1] and DesignAR

[3] demonstrated the extension of visualization beyond the tablet screen through AR and manipulating the AR contents from the tablet. Langner et al. [1] and Reipschläger et al. [3] have not explored the benefits of a tablet+AR interface through an experiment of comparing tablet+AR with a tablet only interface. Such a comparative evaluation could have revealed the benefits and limitations of visualizing multivariate data in a tablet+AR interface. In this research we improvised by exploring the benefits of tablet+AR through a controlled within-participants study against tablet only interface.

We visualized Brain Computer Interface (BCI) time-series data in AbVD and ArVD. Finding salient data points from multiple related time-series data and from time-series data recorded for a longer duration are our use cases for AbVD and ArVD, respectively. In data comprehension context, when time-series data is visualized for a longer duration, it will be challenging to isolate data points in a single screen. If the content is zoomed, users have to swipe multiple times to navigate through the data. Use of focus+context view in ArVD leverages infinite screen space to present large data without screen size limitation. Also, when multiple overlaid time-series graphs are viewed in a single screen, there is a challenge to isolate salient data points due to graphs overlapping with each other. Use of layering in AbVD to present multiple related time-series plots provides better visibility that would otherwise be difficult when those plots are overlaid on each other in physical screen. Our interface supports perceiving complex BCI data (longer duration valence and arousal data up to 7000 epochs) and multiple time-series data that represents features involved in calculation of valence and arousal. An epoch is a slice of EEG signal for a specific duration representing time and frequency. Time-based epoching (One epoch is equal to 0.625 ms) is used in BCI to create slices of signals over a period of time that is large enough to process the signals.

In our research, we evaluated our interfaces by comparing them with tablet only interface for similar tasks in two controlled within-participants experiments. Tablets have toggling, zooming and panning features to analyze large and multiple data visualizations. A comparative evaluation of interfaces helped us to find answers if ArVD enhances comprehension of long-duration time series plots of BCI data, compared to zooming and panning on a tablet. A similar comparative evaluation helped us to find whether AbVD enhances comprehension of individual time series plots of BCI data presented on separate horizontal layers in AR and shows the relationship with each other, compared to presenting them all on a tablet display. Through our experiments, we are also able to point out strengths and limitations of AbVD and ArVD in terms of system usability, cognitive load and user experience.

In my thesis I explore two research questions. The first research question **(RQ1)** that is connected to AbVD is: **Can presenting individual time series plots of BCI data on separate horizontal layers in AR enhance comprehension of each plot and of how they are related to each other, compared to presenting them all on a tablet display?**. Data comprehension in specific context to AbVD means how participant interpret the features involved in calculating valence and arousal data by finding salient data points in each feature presented in layers and comparing the values of the data points i.e valence and arousal, the alpha/beta frequencies of F3 and F4 presented as layers in AbVD interface.

In a controlled study we test a hypothesis (HA), which is a more constrained and testable form of RQ1.

HA1) Placing time-series data in AR layers above a display leads to faster acquisition of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display. and

HA2) Placing time-series data in AR layers above a display leads to more accurate selection of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display.

For our testable hypotheses HA1 and HA2, the respective null hypotheses are as follows: **H0A1)** Placing time-series data in AR layers above a display does not lead to faster acquisition of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display. and **H0A2)** Placing time-series data in AR layers above a display does not lead to more accurate selection of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display.

The second research question **(RQ2)** that is connected to ArVD is: **Can extending the boundaries of the tablet screen using AR enhance comprehension of long-duration time series plots of BCI data, compared to zooming and panning on a tablet?**. In ArVD, data comprehension means to interpret salient data points i.e valence and arousal values presented as a longer duration time-series data(i.e 0-7000 epochs/5.5 minutes) in focus+context view.

Our related hypothesis(HB) is a constrained form of RQ2:

HB1) Presenting long duration time series data in its entirety by extending a tablet display using AR will permit faster identification of salient data points than when using zoom and pan on a tablet display. and

HB2) Presenting long-duration time series plots of BCI data by extending a tablet display using AR will permit more accurate identification of salient data points than when using zoom and pan on a tablet display.

For our testable hypotheses HB1 and HB2, the respective null hypotheses are as follows: **H0B1)** Presenting long duration time series data in its entirety by extending a tablet display using AR will not permit faster identification of salient data points than when using zoom and pan on a tablet display. and **H0B2)** Presenting long-duration time series plots of BCI data by extending a tablet display using AR will not permit more accurate identification of salient data points than when using zoom and pan on a tablet display.

We measured task accuracy and time taken for testing HA and HB for RQ1 and RQ2. Task accuracy and time taken are some of the measures for system usability for a specific task using two or more interfaces [4]. The usability of AbVD and ArVD in identifying salient data points in AR layers and focus+context display can be indicated by relevant measures such as accuracy and time taken to complete the task. There are other measures for comprehension, which we discussed in the limitations. In our research, we are confident in picking task accuracy and time taken as measures for AbVD and ArVD.

Our AbVD results indicated that in terms of accuracy (HA2) in locating salient data points in layers, there is a significant difference between AbVD and tablet only interface favoring AbVD. Though time taken is significantly higher in AbVD than tablet only interface thus not favoring (HA1). In ArVD, there is no significant difference in terms of time taken favoring (HB1), although we found significant difference in terms of accuracy for finding salient data points in focus+context view (HB2). Our research findings would benefit future research and development of hybrid tablet+AR HMD interfaces and for people who work in neuroscience and other fields when analysing BCI data.

Overall, our research on AbVD and ArVD contributed to the hybrid interface research specifically by demonstrating the benefits of using a hybrid interface to present complex BCI data. Our AbVD and ArVD interface added value to the immersive analytics field, showing the use of immersive technologies such as AR/VR/MR to visualize and explore the data. Conventional interfaces such as personal computers, tablets, large screen displays, and curved displays can present a variety of data. However, the performance comparison between the conventional interface and hybrid interface can lead to an indication of aspects where the hybrid interfaces can perform better than tablets and also indicates their limitations. Our within-subject experiment compared AbVD and ArVD with the tablet-only interface to explore the areas where the tablet+AR interface is beneficial for data visualization and analysis. Through our study, we gained insights into participants' experience using the tablet+AR interface and their behavior for different tasks, such as tasks involving different head orientations and resting positions. Our research also indicated aspects of future improvements for the tablet+AR interface for BCI data.

My thesis chapters describe the background work and motivation behind tablet+AR research. The system overview chapter presents the design decisions, motivation from earlier work, the prototyping stage, and knowledge gathered from our pilot studies. The evaluation section describes our controlled-within-subjects study that compared AbVD and ArVD interfaces with the tablet. The data analysis chapter illustrates the qualitative and quantitative data analysis and answers to our hypotheses HA and

HB. The conclusion and discussion chapter portray the results and knowledge gained from this research and its relevance to earlier works.

Chapter 2

Research background

The primary focus of our work is on three areas, augmented reality, brain computer interface (BCI), and hybrid interfaces. Our work is also related to immersive analytics, specifically information visualization in augmented reality. In brain computer interface, we process EEG signals and visualize in handheld interface such as tablet+AR interface. Some of the prior research related to this area are presented in following sections.

2.1 Augmented reality

Augmented reality is the method of superimposing graphical elements in our view of the real world. Augmented reality is used in general industrial applications such as data visualization, manual assembly of circuits, and training (e.g., [24, 26]). AR is also useful in the entertainment industry, such as sports for training and performance monitoring of athletes (e.g.,[27]). AR us also used in advertisement, and marketing areas (e.g.,[27]). Augmented reality evolved over decades for presenting contextual information to the user in the real world. Tatham et al. [16] demonstrated a system that superimposed graphical elements in the real world. The roots of head-mounted displays(HMDs) can be traced back atleast to late 1968 when Sutherland et al. [14] demonstrated the use of head-mounted displays to project 3D images. Earlier research by Caudell et al. [15] illustrates the use of head mounted display called "HUDSET" in industrial applications such as aviation. Recent technological advances in augmented reality paved the way for many commercial and industrial applications for providing contextual information in public places like museums [29], for training and education purposes [30], and entertainment such as gaming (e.g.,[28, 31]). AR applications are getting increasingly popular such as Pokemon Go, a persuasive AR game app for mobile devices [25].

Using augmented reality, we can present contextual information or cues about the subject that can aid in perceiving the details and enhance the user experience. Unal et al. [73] demonstrated the use of location based augmented reality to superimpose digital recreation of historical site over the real one. A drone is used to capture the real world coordinates and render the digital 3D model accordingly on top of the site [73]. Recent research in augmented reality shows that contextual information visualization in AR helps the viewer to gain background information of paintings and historical artifacts in museums(e.g.,[23, 29]). Park et al [29] conducted a study to explore impacts of age and motivation in viewing abstract AR content for artifacts in museum, results indicated higher age can lead to lower satisfaction and positive motivation comes with addition of more features i.e taking pictures, leaving reviews.

AR is also used in visualizing information related to tasks in industrial environment. Satkowski et al. [24] conducted a user study to analyze the impact of the external environment on data analysis tasks in an industrial environment. The results indicated that the background had no significant impact on the user's perception of AR content and task performance. Satkowski et al. [24] also pointed out that task completion time might vary depending on complexity and distraction in the environment, but the impact is not significant. The research in augmented reality. Yoo et al. [23] developed a project that provides contextual information paintings in museum by slicing the image target and presenting abstract information about the component i.e person in the painting. ([23, 29, 24]) gave us valuable insights about impact of diversity, environment and data visualization that helped us to consider above aspects designing our study to evaluate AbVD and ArVD.

2.2 Limitations of conventional displays

Screen size and resolution can limit how displays can effectively support different data visualizations. Pavanatto et al.[4] conducted a user study that compared physical, virtual, and hybrid monitors in different aspects such as task performance, accuracy, comfort, and preference. Augmented reality can be an alternative to adding or enlarging displays to project additional content. Reipschläger et al. [3] created a workstation for designing 3D objects called DesignAR that combines a tablet and augmented reality. Reipschläger et al. [3] stated that AR objects placed close to the display and around the edges of the display have a strong spatial connection to the display. DesignAR [3], and MARVIS [1] show that extending displays using tablet+AR can be helpful for data analysis tasks involving different kinds of visualizations, including maps and charts. The design of AbVD and ArVD is motivated by MARVIS [1], DesignAR [3], and personal augmented reality for large interactive displays [48], where they projected AR content above and around the display.

Pavanatto et.al's[4] compared conventional computers and virtual monitors motivated our selection of aspects that are beneficial to compare, e.g. accuracy and preference. DesignAR's research by Patrick Reipschläger et al.[3] introduced the concept of "augmented display". As per Patrick Reipschläger et al.[3], Augmented displays extend the content displayed in physical monitors into 2D or 3D space in AR.

In immersive analytics, visualizing data in different views can lead to different perspectives on data. Earlier research [64] demonstrated the creation of different visualizations through toolkits in immersive space. Cordeil et al.[64] created a toolkit called IATK for generic data visualization and exploration. In IATK, the user can select data, pick X and Y axis parameters, and create line charts, scatter-plots, and scatter-plot matrices [64]. Cordeil et al. [97] created an immersive system called ImAxes to explore multivariate data. In ImAxes, the axis parameters and data visualization can be changed to get different perspectives of data. Büschel et al. [2] portrayed visual data analysis of user trajectories and event data in mixed reality and conducted an expert feedback session to gain insights about data analysis. The expert feedback highlighted key challenges such as limited field of view and physical constraints when wearing the HoloLens 2 for a long time.

In the IATK toolkit [64], 2D/3D connected dots visualization where multiple graphs overlaid on top of each other in 2D and spread apart in 3D is one design motivation we explored for layering. Similar to the expert feedback study by Büschel et al.[2], we decided to recruit 5 participants from neuroscience to gain insights into their experience with our interface and get expert feedback on the possible future applications of the interface in neuroscience.

2.3 Brain computer interface

The Brain computer interface (BCI) is a system that interprets brain activity and converts it into computer commands. The BCI terminologies used in our research are alpha and beta frequencies, valence and arousal. Alpha, beta, theta, gamma and delta are five frequency bands/rhythms observed in the human cortex. Brain activity can be measured by electroencephalogram (EEG). EEG is the method of measuring the electrical activity of neurons in the brain through a portable BCI device. Beta rhythm is associated with increased alertness or focused attention, and alpha rhythm is associated with a relaxed state [134]. F3 and F4 are electrodes in an EEG device pointed to a specific scalp region. We visualized epoch-frequency plots, otherwise called time-series plots, for our interfaces. They denote frequency values for each epoch (1 epoch = 0.625 ms) from specific electrodes i.e., F3 and F4.

BCI is coined in early 70s when Vidal et.al [66]. EEG is widely used in several research for emotion recognition and neurofeedback (e.g.,[6, 7, 9, 10, 13]). The features extracted from the EEG signals will help in identifying patterns in brain activity. Consumer grade BCI devices like OpenBCI [41], Neurosky [40] and EMOTIV[39] are more commonly available in market. Though data from consumer devices are more prone to packet loss. The EEG data is also used in previous research for evaluating player task engagement when playing video games e.g.([6, 71]). OpenVibe [18] can visualize the brain signal data in live and recorded formats and there are also other scientific tools like Matlab, tableau, Python to visualize and analyze the recorded BCI data. Such visualization tools can help present data in different ways, e.g., charts, graphs, and multiple-linked visualizations. They have different features to interact with data, e.g., linking, brushing, zooming and panning. Although, limitations in terms of screen size and fitting large visualization or many related in a single physical screen is a challenge.

Neurofeedback includes collection of EEG data in a controlled setting where a person is tasked to do perform an operation that can activate certain regions of brain[72]. Ryan Hubbard et al.[65] demonstrated that neurofeedback could help enhance the learning experience in a virtual reality environment through feedback from EEG signals on the state of the learner's mind. Cavazza et al.[72] described three levels of neurofeedback system, first is the target brain area, EEG is each brain area is connected to specific functions of the brain. The second is the sensing device that can capture the brain activity of the target brain area, The third is presenting the signals to the user as an perceivable information.

BCI is also used in medical and industrial fields. Shih et al.[38] in the review highlighted the typical applications of BCI in the medical field. There are three types of BCI, Invasive BCI, Non-Invasive BCI, and Semi-Invasive BCI. They are non-invasive techniques using Electroencephalogram (EEG) are more commonly used for BCI applications to capture brain signals and convert them into commands (e.g.,[36],[37]). Non-invasive BCI is in commonly used headsets such as EMOTIV[39], OpenBCI[41], and Neurosky[40] by placing the device over the scalp of a person and sending the raw EEG signal data from individual electrodes placed in the BCI device to the computer. The platforms such as OpenVibe can connect and receive EEG signal data from the BCI headset[18]. The OpenVibe platform filters the EEG signals using box processing features to eliminate noise and extract specific frequency bands such as alpha, beta, and delta frequencies([6, 18]). Electrodes in BCI device are positioned in different areas of the scalp as per Brodmann's Area to capture brain activity in specific areas[22]. Our background review on applications of BCI and signal processing of EEG (e.g.,[36, **?**, 37, 38]) encouraged us to use signal processing and extract specific features namely alpha, beta, valence and arousal from BCI data for visualization.

In OpenVibe [18], the interaction with data is challenging e.g., seeing salient data points and screen size limiting the portion/number of features e.g., multiple frequencies from sensor nodes. Tablet+AR interface can help to visualize the overall duration of data and navigate through the salient data points. In ArVD and AbVD, we can find a range of salient data points in longer duration and points of interest in multiple related graphs can be viewed in layers.

2.4 Time series analysis in EEG

Time series data means visualizing EEG data as the time-frequency decomposition of one or more frequency bands. In the context of analysis of time series data that are recorded for a longer duration, one practical application we found is seizure localization in epilepsy. It requires large-scale artifact analysis to detect patterns and locate seizure-related features. Lehnertz et al. [141] conducted a study on 300 EEG recordings, and non-linear analysis in EEG helped to locate seizures in different cerebral regions in 80 percent of patients. Koenig et al. [142] mentioned that spontaneous or sporadic EEG activity might not be sufficient to isolate areas in data that describe shorter-duration events. Koenig et al. [142] also mentioned that time markers are needed to describe attributes related to an event that changes over time. A microstate means quantifying EEG signals into smaller duration data, for example, representing 100ms as a single epoch [143]. Konenig et al. [142] also demonstrated creating an artificial signal by combining three signals of different frequencies and times. Kaur et al. [144] reviewed several techniques to analyze EEG signals. One of the most efficient ways for discrete and continuous EEG analysis is wavelet transform, i.e., the conversion of the signal from time to frequency domain leads to the localization of signal patterns.

2.5 Valence and arousal

Valence and arousal are essential features that determine a person's emotional state. Słupińska et al.[7] highlighted the use of The valence, arousal, and engagement factor formula in human behavior. The research also mentioned that neuroscience measurements such as valence, arousal, and engagement factors help study the participants' experience during the VR experiment. The paper by Słupińska et al.[7] is very useful for our research, and we used valence and arousal to extract its values in the openVibe platform. The research also gave us insights into applying neuroscience concepts in controlled experiments.

The valence and arousal values can be calculated from EEG signals using the formula that uses alpha and beta frequencies of F3 and F4 nodes, Gilrado et al. [115]

though it has to be accompanied with appropriate windowing and classification algorithms to get accurate values free of noise. There are consumer grade devices such as Neurosky that can portray direct values such as attention and meditation [145]. EMOTIV epoch plus also can portray metal states such as sadness, anger and joy to the user [145]. We want our AbVD and ArVD interfaces to support different types of EEG analysis in longer duration and multiple time series data not limited to valence and arousal. Hence we did not use consumer-grade devices that give direct indication of emotion states in our research.

Valence and arousal attributes to different emotions. There are research that uses different frequency bands and electrode positions but ours is as per Gilrado et al.[**?**]. Alpha and beta are frequency bands in EEF aid in emotion classification. Dabas et al.[21] demonstrated the classification of emotions from EEG signal frequencies using machine learning algorithms. Dabas et al.[21] also pointed out that alpha, beta, theta, and delta frequencies are associated with specific states, i.e., Alpha frequencies are associated with relaxed states, and Beta frequencies are associated with active thinking or concentration.

We further reviewed other research that used the valence and arousal formula. McMahan et al.[6] conducted a study that used the valence and arousal formula to calculate players' task engagement when the participants played a video game. Though the valence and arousal formula in [6] is derived from [115]. The alpha and beta signals ratio is used to find the different states of brain activity, such as task engagement, when a participant is exposed to a particular scenario, Kamila Słupińska et al.[7]. Chen et al.[10] created a model to process EEG signals alongside the user profile for better emotion recognition. Previous research in BCI eg., [6, 7, 10, 21] that demonstrated EEG signal processing and extracting frequency bands, mainly alpha and beta, application of valence and arousal formula is beneficial to our research in terms of calculating valence and arousal values.

2.6 Feature extraction and data visualization in brain computer interface

EEG technique is non-invasive, means the data can be captured from scalp of head by using pointed electrodes in BCI device. The captured signals from EEG device can be visualized as live or offline data in software platform. In the openVibe platform, the EEG data can be displayed as live or offline as time series graphs (epoch-frequency plots, i.e., epochs on X axis and frequencies on the Y axis [18]. The wave patterns in EEG data can help understand the person's mental state. In previous research, data analysis and information visualization of BCI data have been done for various purposes, such as concentration and meditation when performing activities like studying and playing a video game [19]. In previous research, popular datasets like the DEAP dataset from the publicly available repositories are used for research, e.g.,[21]. Previous research employed different methods to collect data useful for different experiments. These include instructing a participant to do a specific task such as presenting a music video to different users [21], Asking the users to perform guided eye movements, and viewing different images and landscapes [20]. Machine learning algorithms are applied to find patterns in EEG features and train models, e.g. ([20, 21]). . The research ([19],[20],[21]) gave insights about popular datasets for BCI, types of study conducted in BCI and popular tools e.g([18],[40]) for BCI data collection.

2.7 Frequency composition, windowing and ERP signatures in BCI

In BCI signal processing, the most common way to analyze EEG signals is to decompose the signal into individual frequency bands, e.g., Alpha (8-12 Hz), Beta (13-30 Hz), Theta (1-3 Hz) and Delta (4-7 Hz) [126]. The changes in frequency bands can be monitored over a particular time window, e.g. specific milliseconds intervals, to analyze event-related simulations in individual frequency bands [126]. The changes in frequency bands can be visualized and analyzed using a time-frequency plot that motivated us to use time-series plots for presenting our data. Saby et al.[126], in the review paper, summarized several works that portray frequency changes in infants, e.g. [127, 128, 129].

Event-related potential (ERP) is another research area in BCI where stimuli-invoked changes or waveform patterns are investigated. ERP can be measured using EEG signals[131]. Stimuli can be any type, e.g., auditory or visual. Waveform changes in response to stimuli within the particular time window are analyzed to get insights about event-related changes. Saby et al. [131] reviewed several works investigating EEG analysis in Rett syndrome. Saby et al. [131] mentioned that spectral analysis is among the common approaches to analyze resting EEG in Rett syndrome. In spectral analysis, EEG signals are decomposed into bands, i.e., alpha, beta, theta, delta and gamma [131]. Sur et al.[130] described about the types of ERP waveforms are P50, N100, N200 P200, N300, P300, N400, P600 and Movement-related cortical potentials(MRCPs).

Signal windowing in EEG is one of the signal pre-processing steps where the signals are divided into segments based on specific time intervals and frequencies. Covantes-Osun et al. [132] mentioned windowing functions, i.e., Barlett, Kaiser, Blackman, Hanning, Hamming and, Rectwin and presented a technique to find the best windowing function with less signal scattering by finding the euclidian distance between convoluted and non-convoluted signals. Augmented reality is the method of superimposing graphical elements in our view of the real world.

2.8 BCI with augmented reality and other applications

We reviewed past research that included BCI and Augmented reality to find the applications that uses BCI data in AR. EEG data is used in different domains such as medicine, gaming, industry etc. In terms of previous works that used brain signals in AR/VR/XR applications, we found several interesting applications of BCI and AR in medicine. The BCI data has been used with augmented reality to promote hands-free interaction with the system, which is used in domains such as healthcare and industry, e.g.[32, 33]. Kohli et al. [32] reviewed applications of BCI signals and pointed out that BCI with XR is used in robotics and home systems. Hands-free interaction through BCI is one of the BCI applications relevant to Human Computer Interaction. Angrisani et al.[33] proposed a system that included BCI and Augmented reality for industrial monitoring. The proposed system by Angrisani et al.[33] includes interaction with the menu items using BCI signals through the gaze. Zhou et al.[34] demonstrated that BCI signal data is also used in areas of virtual reality, such as desktop VR flight simulation[34]. BCI is increasingly used in neuro-engineering to address motor impairments through BCI-driven robotics[35]. Based on the recent research e.g., [32, 33, 34, 35], we found that BCI data is used for neurofeedback that helps different applications in AR and VR. However, the earlier researches mentioned about did not point to a hybrid platform that helps user to visualize BCI signals and analyze data in more self-explanatory nature irrespective of duration and number of features.

2.9 BrainZebo - A neurofeedback project

In previous work by one of the researchers in our lab for the project called "BrainZebo" encouraged us to explore interfaces that are suitable to visualize BCI data. BrainZebo is a neurofeedback project in which the EEG signals captured live/recorded from OpenBCI device is processed using SVM classifiers to extract valence and arousal values and stream them through sockets using OSC (Open Sound Control) and to VR application. The valence and arousal is visualized in VR in form of light blobs. The color of the blobs, light intensity and music effects changes according to the valence and arousal values. In BrainZebo a separate script in VR application processes EEG signals and computes wave means, max values and left and right means and use them for visualization. Max platform receives FFT (Fast Fourier Transform) values from OpenBCI and converts it to music amplitude for VR application.

During my work in BrainZebo, as a part of preliminary work I explored different ways to compute valence and arousal values directly from the signal processing platform in offline using recorded data and visualize them in more readable fashion when compared to abstract visualization of valence and arousal in BrainZebo. During literature review I read about, Gilrado's et al [115] to compute valence and arousal and I used that formula in OpenVibe to create a signal processing architecture to compute valence and arousal values. The valence and arousal formula is also used in research by McMahan et al. [6] More information about this implementation is presented in sec[3.3.1]. Platforms that can process and visualize the BCI data through time-series graphs are desktop apps such as openVibe. In OpenVibe, we found examples of game applications that uses BCI data for controlling a game object in virtual reality [77].

2.10 Physical displays

Conventional displays such as curved screens have their benefits. They can offer greater immersion, but portability is limited, e.g., a desktop computer with curved screen. Previous research also pointed out works that compared different displays in terms of user experience. Zannoli et al. [133] ran a study that compared flat screens with curved displays in terms of field of view, and the results indicated that curved screens could offer better immersion by increasing the field of view. When different types of displays had its own benefits, we chose HMD i.e., HoloLens 2 for extending our display in AR. HoloLens 2 has a better field of view. In AR devices such as HoloLens 2, the infinite screen space in AR and portability can be leveraged. There are also options in Virtual reality (VR) where we can visualize data and the position of content can align themselves according to head position of the user called simulated head parallax e.g., FishTank VR [139]. But it might require complex head movement tracking architecture and user has to be in total immersion in VR. Cubelos et al. [140] proposed a methodology to analyze quality of experience during motion parallax using multiple video view in VR, and one of the results pointed out user's movement speed can affect the perception of content in VR. We chose AR because the user need not be total immersion with digital surroundings all the time and AR can act as a natural extension to the contents presented in physical display.

Transparency is one of the advantages of using Holographic displays, and through transparency, the user will not sense the presence of a physical screen when perceiving the visualization [134]. We used HoloLens 2 for the same benefit, a fully functional holographic display without the aid of an HMD device is still in the early stages of development. Nakamura et al. [134] developed a small 360-degree cylindrical and transparent holographic display for realistic 2D images. Large displays can offer immense screen space to visualize the content and interaction options to manipulate the data. Ardito et al. [135] pointed out that large screen displays are generally placed in fixed public settings and can also aid in visualizing datasets and enable the user to get new perceptions of data. However, the larger screen size, reduces device's portability. Smartphones are easily portable, though they offer limited support for visual data exploration. Urushiyama et al. [136] proposed screen extension technique for smartphone screens where the focus region and the smartphone's off-screen contents are presented in the external display. Despite offering portable options and utilizing an external display for off-screen data, the external display is a physical display that is limited to use in meeting rooms and desktop computers.

2.11 Hybrid interfaces

. The hybrid interfaces connect different types of devices to perform a task. Hybrid interfaces exchange data among themselves to perform a task. We reviewed several works in the past to know more about interaction between multiple devices that assist in performing a task. Research by S.Satao and Harihara [42] demonstrated a tablet application that uses CT data to visualize tumors in augmented reality during liver dissection. The hybrid environment can enable the user to control the virtual objects presented in the head-mounted display. Research by Wang and W. Lindeman [43] demonstrated Tablet + HMD to control virtual objects presented in the display. The same task can be performed simultaneously with two or more collaborating applications in a hybrid environment, such as desktop and virtual reality, when they share similar data visualization and code closely coupled to work synchronously [44].

Some examples of hybrid interfaces in educational applications, e.g., iVRNote [46], demonstrated a hybrid interface to assist in practical scenarios such as taking notes in a virtual learning environment. In iVRNote [46], the tablet device can work synchronously with notes displayed in VR and adjusts its position based on the tablet position. When the student takes notes in the VR session, he simultaneously interacts with the note in the VR and Tablet. The technique they applied to achieve the synchronization is through electromagnetic sensors in the tablet that communicates the position and orientation of the stylus to the VR. In MARVIS and DesignAR, tablet computers work synchronously with Hololens in response to touch surface from tablets e.g.,([1, 3]). MARVIS uses websockets to communicate to 2D visualizations projected n Hololens in response to touch events from tablet.

The previous works on hybrid interfaces, i.e. [42, 43, 44] gave us some idea on communication between two applications on different devices to perform a task. Our research uses the tablet touch surface and its user interface to communicate to augmented reality layers in the Hololens application. Among the other previous relevant research MARVIS [1] design was preferable in our research for communicating between a tablet and AR device through websockets.

2.12 Extended physical displays using augmented reality - Relevant works and challenges

The idea of using mixed reality with displays for creating hybrid distributed user interfaces was first explored in the 1990s by Feiner and Shamash [8]. Integrating physical and augmented workspace to perform 3D modeling using a tablet + HMD was explored in DesignAR [3]. In DesignAR [3], the researchers used the tablets above and around the display to generate 3D models in response to the user's hand drawings on the tablet screen using pen and touch techniques. The other recent research outlines the potential design space for using the above and around the display for data visualization with the help of use cases. However, it does not evaluate the usability of the study using controlled experiments[1]. In MARVIS, the researchers projected additional AR content with the tablet display, enabling the user to better understand specific visualizations with the additional AR context provided above, around, and between tablet displays [1]. MARVIS also demonstrated the seamless integration of AR and tablet display in extending visualizations from tablet display through AR and manipulating AR visualization and tablet visualization simultaneously from the tablet [1]. Our research compares tablet computers and tablet + HMD for data analysis and comprehension. Benjamin Bach studied the effectiveness of data exploration in augmented reality with immersive tangible AR with other methods such as analyzing the data in tablet AR and desktop computers through a controlled experiment [47].

The study by Benjamin Bach also showed that immersive AR with tangible markers perform better in terms of accuracy and time for tasks that require precision and interaction [47]. We also incorporated a set of training tasks to train participants before starting the primary set of experiments. Training tasks can help participants coordinate AR and interaction perception [47]. Over-plotting is also an issue even with a larger display when displaying a large volume of data [48, 49]. In our research, to view extensive time-series data, we project a large portion of time series data in augmented reality around the tablet display with a portion of visualization presented on the tablet. One of the existing methods to overcome the display of complex data is by using focus + context displays which can zoom in on the selected focus area through an interactive lens [50].

2.13 Data visualization in extended displays

In conventional displays, The amount of information displayed simultaneously is impacted by technological limitations such as screen size, weight, and fashion [58]. Distinguishing important information from other information is difficult when the whole visualization is presented [58]. In MARVIS the researchers extended the visualization beyond screen in augmented reality [1]. Some earlier researches used in map application in mobile used focus+context and overview+detail display techniques to project large map data in a concise way, highlight important information and enable better navigation through data. Such as the research by Cockburn who mentioned interfaces such as Google maps using overview + detail, zooming, and focus + context to view map information [58]. Our research used focus points to navigate through extensive time-series data. We used touch interaction with the tablet to interact with the contents in the tablet and manipulate visualizations in the tablet and AR. Touch is a prevalent mode of interaction offered by tablet devices and an important design consideration when designing an interface [60]. It is more suitable for our tablet + HMD interface.

Limitations of the screen size of the devices can also make visualizing of essential portions of data challenging, especially when we zoom in and navigate through them. Some earlier approaches to address the screen limitation when we zoom in are off-screen visualizations such as Wedge [51] and Halo [52], which can clip important information to the edges of the screen when the map content moves. The situated and embedded visualization in augmented reality can also visualize a portion of data close to the data referent, adding more context to the visualization by displaying additional information adjacent to the data visualization.

2.14 Spatial alignment of AR displays

Combining conventional displays with augmented reality could help in viewing complex data. Reipschlager et al. [48] demonstrated the use of augmented reality to present contextual visualizations for information visualization in large displays. Reipschlager et al. [48] also pointed adopted spatial alignment of AR data in front of the display and edges of the display that made us believe above and above display could help present complex data visualization limited due to screen size. Besides smaller displays, there are significant shortcomings even for larger displays in terms of the volume of data displayed on the screen. Increasing the size of the screen might not always be a good option to present large data [48]. Willett et al. [53] demonstrated situated and embedded AR visualization using spatial attributes adjacent to the physical spaces that could help analyze the data better.

In our research, The alignment of AR content is on top of the tablet screen for the above display interface. Whereas, the alignment of AR content is closer to the edges of the tablet screen. P. Reipschlager and R. Dachselt [3] defined the spatial proximity of AR content close to the display and around the edges of the display in DesignAR. AbVD and ArVD are designed with the notion that the content we present in augmented reality should demonstrate a strong connection and precision to the physical display. Reipschlager et al. [48] pointed out that connection and precision are essential aspects of better spatial alignment and placement of AR on the center, left, right, top, and bottom of the screen for extended data visualizations. Incorporating augmented reality in the central zone can provide additional spatial dimension to the visualization [48]. In our above display, we project four layers of AR above the tablet display to visualize different BCI time series data. We believe the spatial position of AR in above and around display is important to perceive the multivariate data in augmented reality. Earlier researches pointed out that the spatial positioning of AR content in the center, left, right, top and bottom is proper even for smaller screens[48].

The spatial alignment of AR layers in research involving physical displays and AR HMDs (e.g.,[1, 48]) motivated us to use the above display and around display paradigms for our research. The MARVIS [1] and DesignAR [3] researches gave us indepth understanding about the tablet + AR HMD interfaces and use case scenarios of augmented displays that influenced our work.

The common issue in visualizing large and complex data is over-plotting when we try to fit in more data into visualization that makes it difficult to read([48, 49]). Some approaches in AR such as projecting the data in layers could make the data more readable, and the elements projected in the layers could help in data comparison [48]. To make the AR layers clearer, controlling the transparency and toggling between layers whenever necessary can make the user read the content better [48]. Colors play an important role in distinguishing layers, and In our research, we used only primary colors with background transparency which can distinguish a layer clearly from the others. The color quality of AR is lower when compared to other conventional displays such as computers, and the background might impact the effectiveness of visualization [54]. Augmented reality is useful to visualize relationships and compare different visualizations [48, 59]. Our research compares valence, arousal, and Alpha and Beta frequencies of F3 and F4 sensor nodes. The challenge that may arise when comparing visualizations is the size of the items compared or the complexity of the items [59]. In our research, we compare four visualizations in the above display and study the interface's strengths.

2.15 Immersive analytics

Immersive Analytics, in general, is multi-disciplinary that combines popular domains such as AR, VR, HCI, and tabletop for exploring design interfaces suitable for better data visualization and comprehension [55]. The most important benefit of immersive analytics is making use of the physical spaces effectively around the user to visualize the data when compared to viewing the data in flat 2D surfaces like computers [75]. In order to understand the effectiveness of immersive interfaces, we need to understand the experience of the user when they perform different tasks using the interface.

Accuracy and time taken to complete the tasks are some important measures that will portray the task effectiveness of the visualization [75]. Comparative studies between the two immersive interfaces provides more insights about the ideal environment for the users to perform the tasks. Bo Sun et al. [76] compared two types of immersive interfaces that vary on visualization, mode of interaction and navigation indicated that immersive setting involving limited physical movements and interaction through gestures is a good setting for small spaces for everyday use. The research by Bo Sun et al. [76] also motivated us to adopt an ideal setting for the experiment i.e seated with limited movement to navigate through the data.

Exploring the feasibility of using the same interface for different types of domains for immersive analytics is also a suitable research area that can be explored [55]. Our research used two types of data: BCI and Space syntax. The selection, navigation, changing, and filtering tasks are among the core modalities of immersive analytics [56]. The interaction types we are motivated to use in our research are selecting the AR visualizations from the tablet, toggling ON/OFF one or more layers, navigating through the data, and selecting specific focus points.

Earlier research demonstrated the effectiveness of using a hand-held device to manipulate data underlying visualizations presented on external displays, such as the research by Louis-Pierre et al. [62]. The interaction and manipulation of digital objects projected on a distant screen from the smartphone through gestured called ASP (Around the smartphone) technique [62]. In the same research [62], two other techniques to manipulate digital elements in distant displays called OSP (On the smartphone) using fingers and WSP (With the smartphone) using the rotation of the device compared to which audience preferred using the WSP technique. In our research, we manipulate the 2D AR layers using touch and swipe interactions from the tablet.

2.16 Existing tools and platforms to visualize BCI data

When there are tools to process and visualize data in physical displays, visualizing BCI data in hybrid platforms such as tablet+AR gives new perspectives during data analysis. Looking at BCI data present in AR layers from different head orientations and resting positions when the features related to valence and arousal can aid in isolating a specific data point/peak, say valence, and check the values of other features alpha/beta values of F3 and F3 at the same point. When a large time-series data unhindered by physical screen size is displayed, that can help the user to find a number of data points within a specific range, and we can see the whole visualization clearly. In OpenVibe or OpenBCI when we run the program to visualize signals, separate windows or single window visualizing the signals will be displayed and it gives us an overview of the signals and its difficult to understand related features and identifying individual data points.

Other analytical platforms such as Tableu [94, 95] can help creating visualizations for BCI such as line graphs for time-series data and we can use linking, brushing and clicking on individual data points to read the values and present individual line charts in single window, Though as discussed in introduction screen size limitation depending on device type still persists. It motivated us to create a the hybrid environment combining tablet+AR to visualize BCI signals as time-series graphs and through layering and focus+context technique we can present BCI data irrespective of duration and number of features. Our approach combines brain-computer interface and hybrid displays that can potentially benefit brain-computer interface domain by opening doors that enhances the perception of BCI data using hybrid displays. Our work can be first step to motivate future work to use hybrid interface such as tablet+AR to visualize and analyse BCI data.

2.17 Design choices

Tablet + AR

The design choices for AbVD and ArVD is adopted from MARVIS [1] and DesignAR [3]. The tablet is portable and the previous research [1] and [3] that utilized focus+context displays demonstrated that the augmented reality can be used to manipulate and extend visualizations beyond the boundaries of tablet by using augmented reality from HMDs i.e HoloLens 2. Our choice for using AR is to leverage infinite screen space, and users need not be in total immersion, e.g., VR, to explore the time-series data. AR can act as a natural extension to tablet screens, which made us choose AR over other technologies.

Suitable placement of AR contents in AbVD and ArVD

When we present contextual information in AR in addition to physical display, the position of the AR content relevant to the content displayed in physical monitor plays an important role to demonstrate its relation to the visualization in physical display. For example in [48] the context information in AR about a bar chart is placed in a vertical position close to the bar chart in physical display to illustrate that the AR content points to this specific bar chart in large screen[48]. In MARVIS[1] the use case scenarios portrayed the placement of AR content +(charts) above the display and close to edges of display (map extensions) that are useful for our research to position contents in AbVD and ArVD. In MIRIA, the visualization of user's position and interaction data in AR is visualized in close proximity to the content displayed in interactive surfaces[2]. In ArVD to visualize a longer duration time-series data, using AR to extend the focus region in the tablet is a suitable visualization paradigm to portray entire time-series graph to the user. In AbVD when we place the AR layers close to each other above the display it can help us adjust our head-orientation and view data from different angles to get different perspectives.

Interaction techniques

Tools such as IATK [64] served as a reference for analyzing the data visualizations in immersive space i.e., Line charts. Fisher et.al.,[96] pointed out three principles of visual representation(adopted from [102]), appropriateness, naturalness and matching principles. In addition to visual representation, Fisher et.al., [96] also pointed out interaction technique is important to create a meaningful dialogue between visualization and researcher. Time-series data is suitable to visualize valence, arousal recorded for longer duration as per matching principle. Selection, navigation and finding location of data are some of the common tasks in context of time-series data in immersive analytics [90]. Tablets can act as interaction surface from where contents in AR can be manipulated [1]. We adopted selection and navigation techniques in AbVD and

ArVD to manipulate AR content. We adopted extended visualization of map path from MARVIS [1] and DesignAR [3] as a baseline for layering and focus+context techniques.

2.17.1 Why BCI data?

Our motivation to use BCI data is tied to the previous work done on BrainZebo that portrayed abstract visualization of valence and arousal in the form of light blobs. In our research, we are motivated to present data that lead to the calculation of valence and arousal more generically, i.e., time-series, to help the users perceive the data, e.g., finding the highest peak in time-series data, comparing the graphs and isolating the data points. We acknowledge that time-series is more generic and applicable to different domains, which allows us to use AbVD and ArVD for different types of time-series data. In addition, the long-term goal of ARTIV research is to compare different data visualization techniques in AbVD and ArVD for different types of data, i.e., BCI, Space syntax and geospatial visualization.

2.17.2 Resting position

Our AbVD and ArVD interfaces are portable, and we have a QR code on the side of the tablet that can place the AR layers closer to the physical display. With the continuous tracking feature, AR layers can move with the tablet. In our study, the participants performed most of their tasks in the seated position, and we made observations if they were tempted to move around to explore data for any task. We tested only evaluated AbVD and ArVD interfaces is different resting positions, e.g., stand up and look down, seated view from an angle and seated and use single layer, though we did not have any specific tasks that specifically asked the participants to pick up the tablet and move around to explore the data.

2.18 Summary of background work

Previous research MARVIS [1], MIRIA [2], DesignAR [3], and Personal augmented reality for information visualization [48] provides evidence that physical computers with augmented reality can aid in data visualization and data analysis tasks. Alignment of AR content are motivated from the works [1, 2, 3, 48] that lead to placement of AR layers in AbVD and ArVD. Interaction techniques in AbVD are motivated from [90, 91]. Previous work in brain computer interface of using EEG data to compute valence and arousal [6] encouraged us to compute valence and arousal from recorded BCI data. The comparative study performed in [4] encouraged us to compare AbVD and ArVD with physical monitors. Recruitment random participants from different background, level of experience with AR/VR and 5 expert participants from neuroscience will mitigate bias in our study. In next chapter we will learn about system design process.

Chapter 3

System overview

In this chapter we present design and implementation of AbVD and ArVD interface.

3.1 Overview of AbVD and ArVD in ARTIV-BCI

Our interfaces AbVD and ArVD consist of Microsoft surface Pro 3 tablet and HoloLens 2 device. Tablet comprises of a web application to visualize the BCI data and communicate with AR layers. In AbVD, we can toggle on/off and switch time-series graphs in AR layers from the tablet. In ArVD similar to AbVD we can toggle and switch the graph. In addition we can use focus points and shift-left/shift-right to navigate the time series graph. In ARTIV-BCI we have menu to select AbVD or ArVD visualization and a toolbar to turn on/off QR tracking to anchor the AR layers close to tablet.

We used pre-recorded EEG data from OpenVibe, processed the EEG signals and visualized them as time-series graphs, i.e., line graphs in AbVD and ArVD. In AbVD, alpha and beta frequencies from F3 and F4 sensor nodes, valence and arousal values derived from alpha and beta frequencies of F3 and F4 are presented in four AR layers. In ArVD, A longer duration valence and arousal values (0-7000 epochs) are displayed in AR. The AbVD supports finding salient data points in different layers and comparison of data points in each layer. User can view and analyse the graphs in different resting positions i.e., seated position from an angle, stand up and look through the AR layers, and toggle on/off layers in AbVD. The ArVD supports finding multiple data points across the range of time-series data using focus+context view by clicking a specific epoch from the focus point.

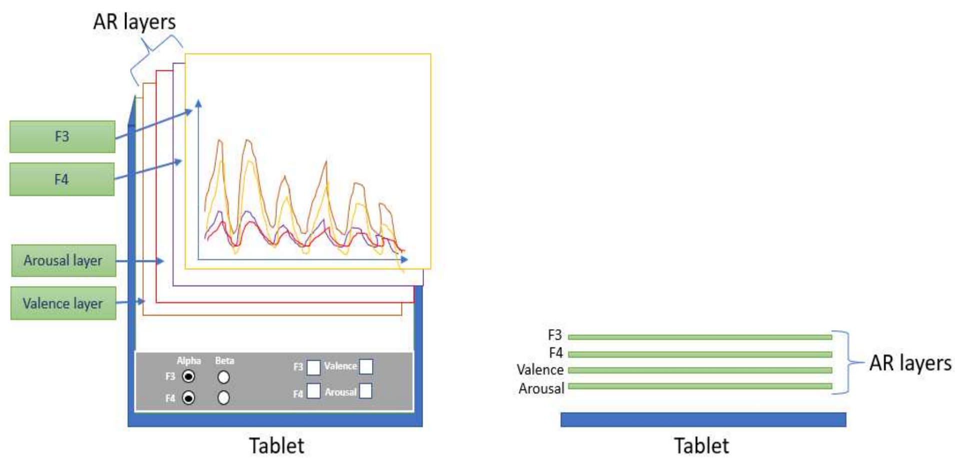


Figure 3.1: Overview of AbVD

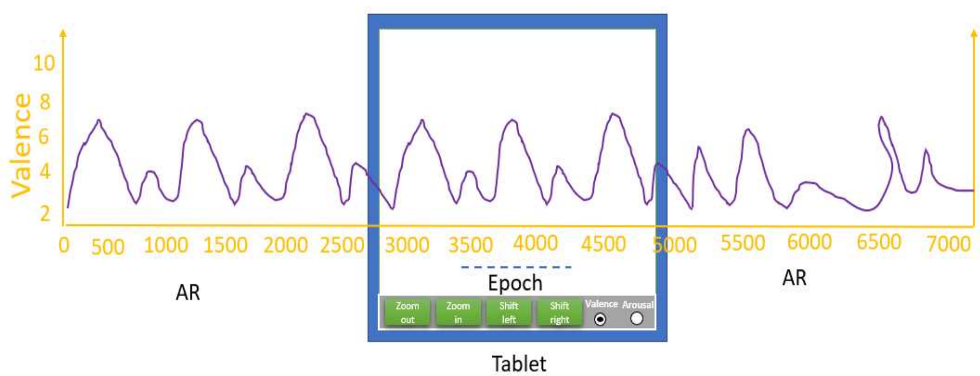


Figure 3.2: Overview of ArVD

3.2 Design

In our research group ARTIV (Augmented Reality + Tablet Information Visualization), three researchers were involved in implementing Tablet+AR interface to explore three types of data. I (Hariprashanth Deivasigamani) implemented AbVD and ArVD for BCI data. Other researchers, Ramanpreet Kaur and Hubert Hu implemented similar techniques for space syntax and geospatial data visualization using tablet+AR. Each researcher was responsible for collecting data with respect to their domain. Throughout the system design phase, We collaboratively brainstormed ideas using Miro board [104], created UI sketches and evaluated designs.

3.2.1 Initial brainstorming

We used Miro board for brainstorming ideas for software platforms, design ideas, features that can be presented, challenges and findings from previous works on hybrid interfaces. The brainstorming phase helped us to exchange our thoughts and ideas. This phase also allowed us to discuss freely and gather feedback to further refine our ideas for sketching the AbVD and ArVD interfaces. A snapshot of brainstorming from miro board is presented in Figure 3.3.

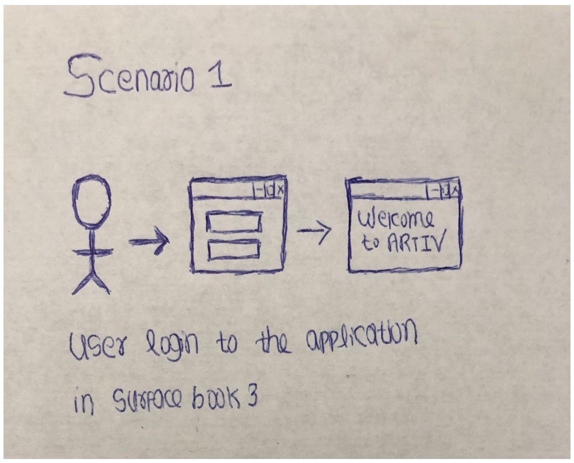
3.2.2 UI sketching

In this phase we drew UI sketches (paper and pencil prototypes) as can be seen in Figure 3.4. In the sketching phase, we specifically considered the previous work done in tablet+AR interfaces and ideas regarding our interface limited to our research objectives. We came up with design sketches of AbVD and ArVD. We also derived use cases to explore user interaction with our application and considered different placements of AR layers.

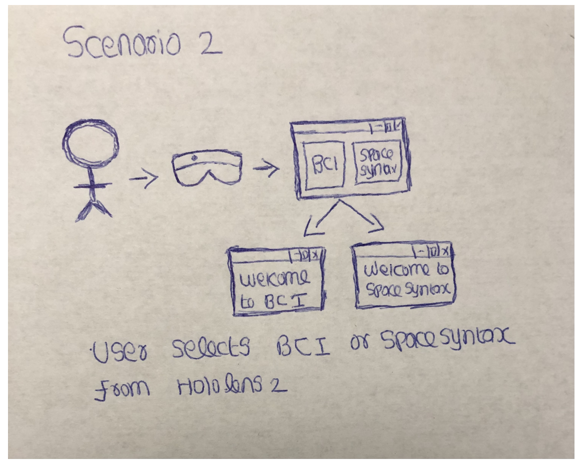
3.2.3 Low-fidelity prototype

The initial prototype phase involved creating BCI visualizations and presenting them on HoloLens 1 device. We explored initial ideas for visualizing BCI data in the tablet+AR interface as can be seen in Figure 3.5(a) and 3.5(b). We also explored multi-monitor concept to visualize time-series data (Figure 3.5(c)). To arrive at a

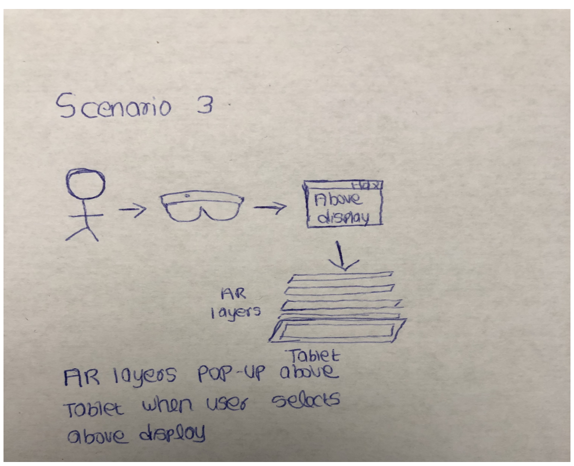
Figure 3.3: Brainstorming using Miro board



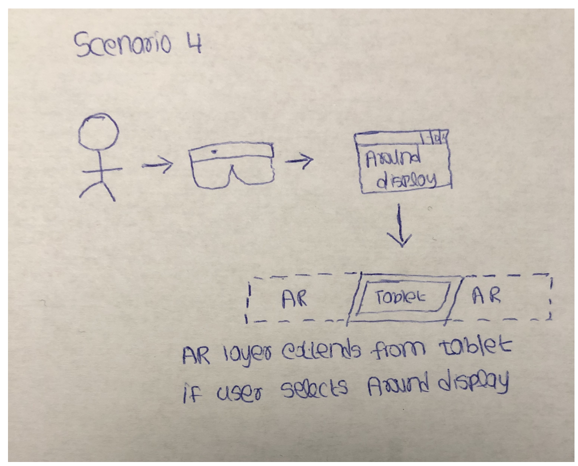
(a) User logs in to application



(b) User select the data

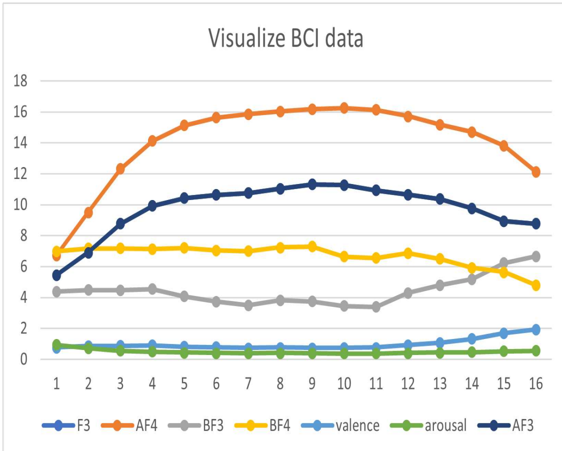


(c) User selects above display

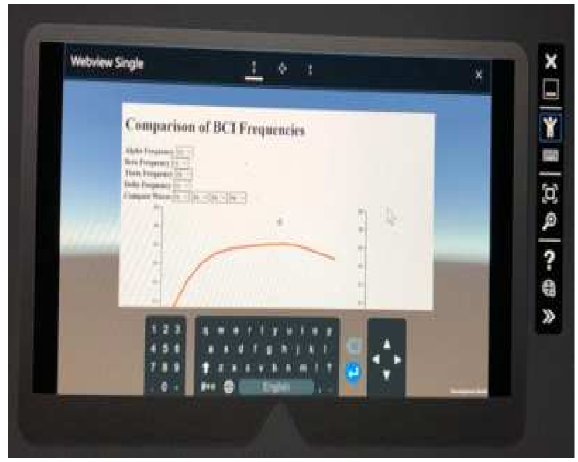


(d) User selects around display

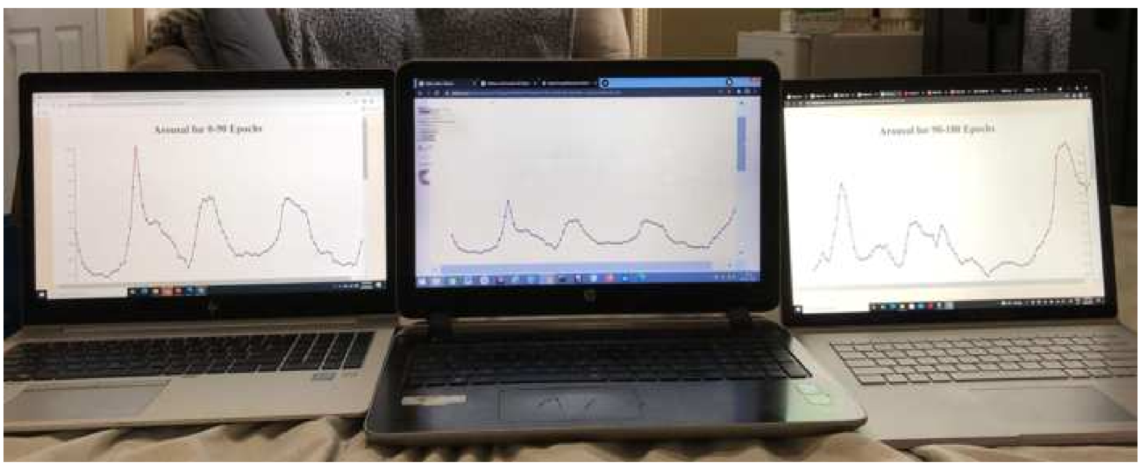
Figure 3.4: UI Sketching



(a) Visualizing Alpha/Beta values of F3 and F4 with valence and arousal values



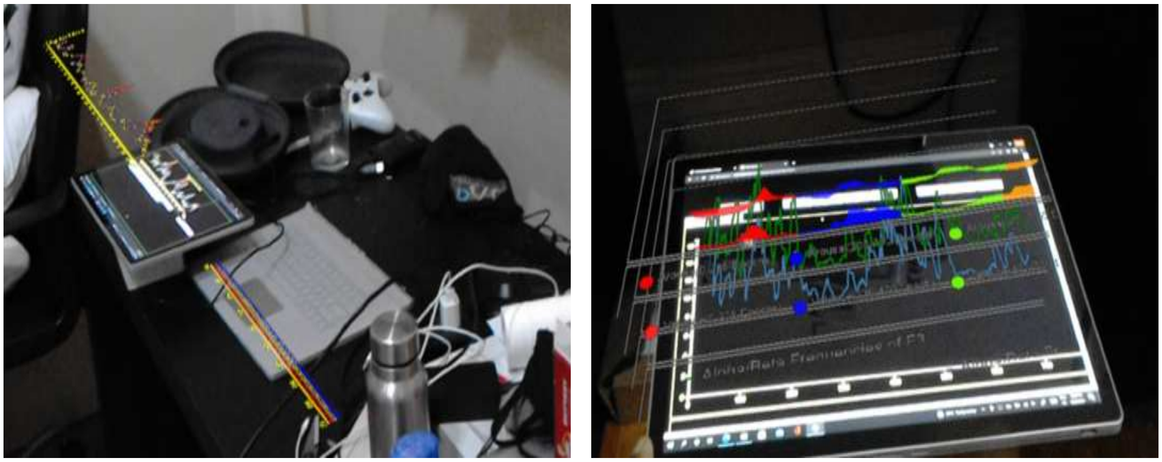
(b) Deploying BCI data in Hololens emulator



(c) Multiple monitor concept for shared visualization

Figure 3.5: Low-fidelity prototype

standard design for AbVD and ArVD, We started with prototype sketching, followed by creating a time-series visualization using the D3 package in JavaScript. We deployed the web application using Webviews on the HoloLens. We wanted to compare AbVD and ArVD against a common portable configuration (i.e., a tablet on its own), and this allowed the same seated configuration, screen resolution, and UI controls in all experimental conditions. After the low-fidelity prototyping phase, we had clearer ideas about how to design and implement AbVD and ArVD.



(a) ArVD (b) AbVD

Figure 3.6: High-fidelity prototype

3.2.4 High-fidelity prototype

During low fidelity prototyping for AbVD and ArVD, we derived design decisions to present four layers of time-series data in AbVD and a longer duration time series data in ArVD. We built a stable AbVD and ArVD interfaces with basic functions such as moving the time series data, changing the alpha and beta values in the layers, and toggling the layers. In anticipation of the comparative evaluation presented in the following chapters, we refined the use-cases for the AbVD interface to focus on different features involved in calculating valence and arousal as time series visualizations on different AR layers. In the ArVD interface, we consider a longer duration of time series data that extends from the tablet's edges using augmented reality. A snapshot of AbVD and ArVD interfaces at this phase is presented in Figure 3.6.

3.2.5 Design Testing and Feedback

We conducted pilot tests with four HCI grad students and faculty members who provided feedback regarding the tablet+AR and tablet-only interface. We made upgrades to the interface after each pilot test. The evaluators expressed that if the time-series data is of longer duration, i.e., 0-7000 epochs, then tablet+AR can be beneficial in terms of adding more context to the screen through AR than a tablet-only interface to view a longer duration time-series graph. For the above display interface, participants mentioned that if the time series graphs are visually distinguishable using different colors and thickness of the lines, that will add to better information perception. In the above display, we presented multiple time-series graphs from 0-2000 epochs with axis labels on each layer.

3.3 Implementation

The data we used to create visualizations is pre-processed from the openVibe platform. The BCI signal data is pre-recorded data freely available in the openVibe platform for development and research [18]. The pre-recorded data is available in GDF format. The BCI signals from the pre-recorded data are processed in openVibe using box processing [18].

3.3.1 BCI data collection using OpenVibe

We used a pre-recorded sample dataset named "real-hand-movements.gdf" available for free in the openVibe platform created by INRIA. We treat this data set as black-box. The dataset comprises of low-level data(raw frequencies) from a 9-electrodes (F3, F4, C3, Cz, C4, P3, P4, O1, O2) that allowed us to derive medium-level data(alpha and beta frequencies) from F3 and F4 nodes and then to high-level data(valence and arousal values). We picked frontal nodes F3 and F4 as per the asymmetric frontal activity hypothesis in Gilardo et al. [115] work, where left frontal activation and right frontal activation are associated with negative and positive emotions.

We used time-based epoching (1 epoch = 0.625ms) to capture many data points for our time-series visualization. The epoch setting is derived from BrainZebo project which gives continuous neurofeedback throughout the duration the participant is wearing the BCI headset. We applied channel selectors to select F3 and F3 sensor nodes and bandpass filters to discard unnecessary frequencies and to capture alpha (8-12 Hz) and beta (12-30 Hz) frequencies. We averaged the signal into epochs (1 epoch = 0.625ms). The epoch window is very small in our case since we wanted to extract around 7000 data points. To perform a simple calculation in the alpha and beta frequencies, We applied valence and arousal formulas from Gilardo et al.[115] mentioned below in a simple DSP signal processing box and generated the valence and arousal values. Our signal processing architecture is presented in Figure 3.7.

arousal = $(bF3 + bF4) / (aF3 + aF4)$
valence = $(aF4/bF4)$ - $(aF3/bF3)$
a = alpha frequency, b = beta frequency

We did not perform logarithmic power representation to compute the power of alpha or beta within a specific window, as proposed by Ansari et al.[118] since our data is recorded for longer duration. We applied the valence and arousal formula to each epoch, i.e., 0-2000 epochs in AbVD and 0-7000 epochs in ArVD, and visualized the data in the form of a time-series. The rationale for this approach is not to convince BCI researchers to take this approach to compute valence and arousal but to demonstrate how the higher level values are derived from raw signals.

We acknowledge the limitations regarding accuracy in valence and arousal values and pre-processing steps e.g., windowing, isolating portions with stimuli, application of algorithms, to get cleaner values for valence and arousal derivations that are free of noise artifacts. There are other forms of valence and arousal derivations possible that require other sensors. We also acknowledge the use of consumer devices to get direct emotion values e.g., Neurosky that gives attention and meditation values and EMOTIV EPOCH+ that displays emotions. Though values from consumer devices are not suitable for our research since we would like to demonstrate the EEG signal analysis from raw frequencies and visualize the time-series in AbVD and ArVD. Some details from this dataset are missing, such as the scenario when recorded, timestamps of stimuli. However, this stands as example to generate valence and arousal values from raw signals. Our research in this phase is more about BCI data visualization in AbVD and ArVD interface than an more specific use E.g., in a medical application. We acknowledge the limitation of not using classifiers such as SVM [113, 107], Logistic regression [111, 112] and LSTM [109, 110] to identify accurate valence and arousal quadrant or distinction between high/low valence and high/low arousal. However using classifiers and measures to remove noise artifacts from data are attributed to future work.

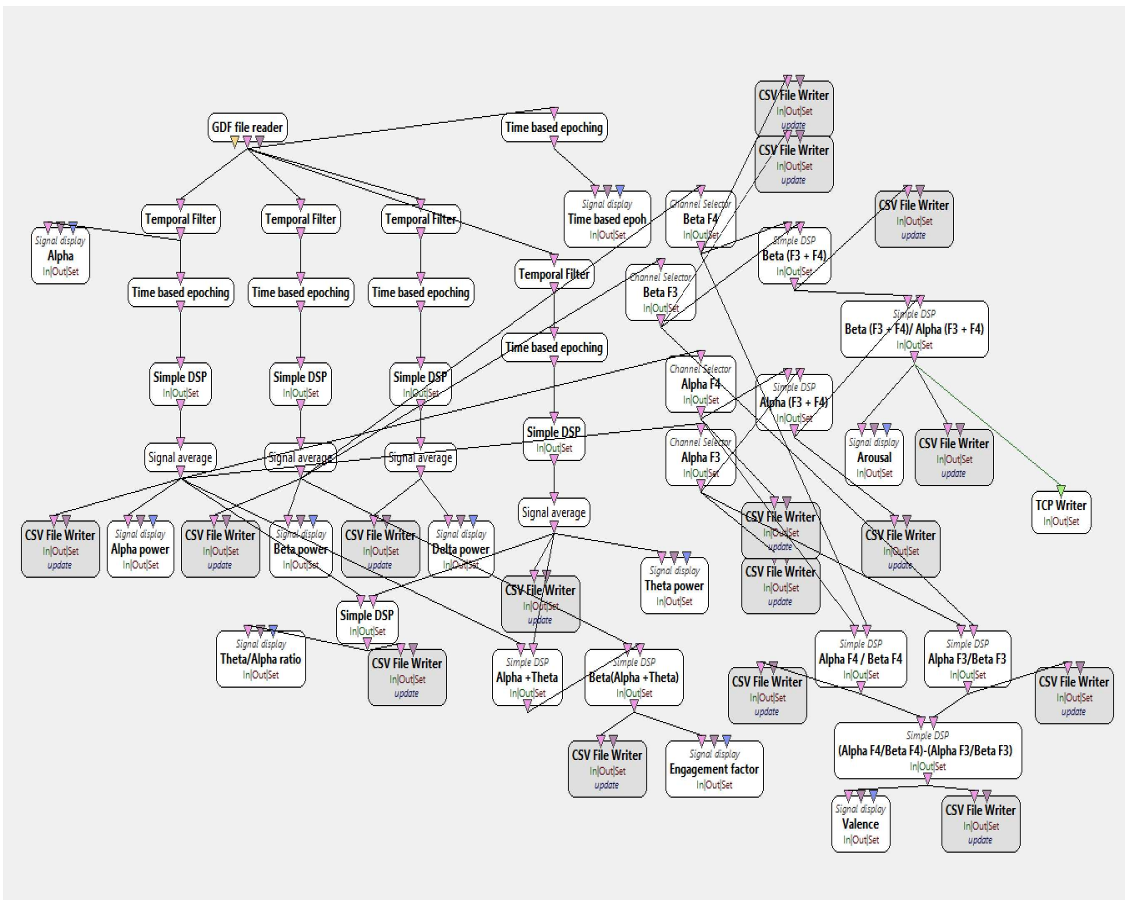


Figure 3.7: Signal processing architecture in openVibe to capture alpha, beta frequencies of F3 and F4, valence and arousal values

3.3.2 Visualizing BCI data on the tablet and HoloLens 2 using D3 js

We created the time-series visualization of BCI data in a web application using the D3.js [61]. We used the Edge browser to run our web application. The X and Y axes are labelled in the web application according to the feature visualized. In ArVD, a portion of a time-series graphs in the focus region is rendered on tablet and the remainder of time-series graph is rendered in AR. In AbVD, four time-series graphs are presented in AR. D3.js is used to visualize time-series graphs on the AR layers (Webviews). On the tablet display we have radio buttons to switch between Alpha and Beta values of F3 and F4 and toggle buttons to toggle on/off the AR layers. We used Unity 3D to build ARTIV-BCI application for HoloLens 2. We designed the AR layers using Webviews and visualized BCI data for the AbVD and ArVD. Webviews is an asset in Unity 3D that can render a webpage in HoloLens 2.

3.3.3 Communication between the tablet and HoloLens 2 applications

An XAMPP server [98] is used to run the web application. The Pagekite software [99] is used to create URLs for the web application. The connection between the tablet web application and the HoloLens 2 application is established using Websockets [100]. The websocket port will listen to the IP address of the web application to monitor incoming broadcast messages between the tablet and HoloLens 2.

3.3.4 Aligning AR content with the tablet

We used QR tracking package from Nuget [103] in Unity 3D to scan a QR code attached to the right side of the tablet (Figure 3.8). QR code align the AR content with the tablet. The QR toolbar in the HoloLens 2 application has a button to start and stop QR tracking. AR content move with the tablet when the QR tracking is enabled. QR code attached to tablet as seen in Figure 3.8.

3.3.5 Transparency in AR layers

In the design phase we decided to make the AR layers transparent in order to enable the users to see through layers of time-series graphs without obstruction. We used canvas and made the background of web pages black in AR layers. Webview has a

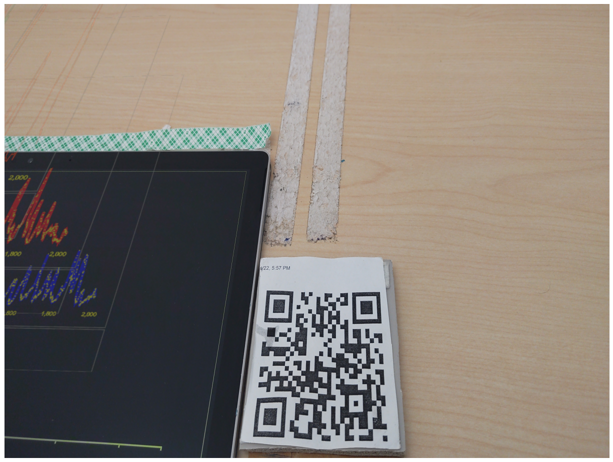


Figure 3.8: QR code attached to the tablet to align the AR contents

feature to make the black background transparent in HoloLens 2, and ensured that this allowed the layers to become visually integrated by viewing them from above. The background was also transparent for ArVD, as doing so made the AR content appear to be more integrated with the tablet focus region.

3.3.6 Deploying HoloLens application

To deploy the application to the HoloLens 2 we built the UWP (Universal Windows Platform) solution in Unity 3D and deployed the application via Visual Studio 2019 when the HoloLens 2 was connected. Once the application was deployed to the HoloLens 2 and executed, a menubar appears as seen in Figure 3.9 where we can select AbVD or ArVD using an air-tap gesture. We can turn on QR tracking from the toolbar to scan the QR code and anchor the AR content to the tablet's position and orientation. The size of the AR layers in AbVD is equal to the dimensions of the tablet screen. In ArVD the height of the AR layers is the same as the tablet screen but the width extends to 6.25 feet to left and right of the tablet to support visualizing longer duration data. Menu to select AbVD and ArVD along with QR tracking is as seen in Figure 3.9.

3.3.7 AbVD

This section [3.3.7] and the next section [3.3.8] give a detailed description of AbVD and ArVD, respectively. AbVD is comprised of a tablet and four AR layers above the

Figure 3.9: Menu for above and around display with QR tracking

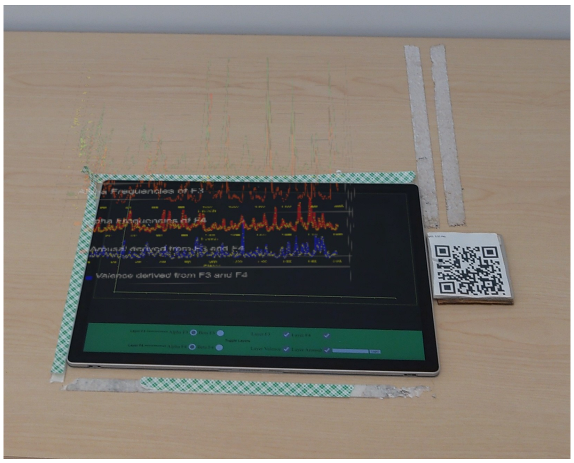
tablet display [Fig 3.10]. In each layer a separate BCI time series data visualization is presented. Projecting data above the display is demonstrated in MARVIS for tablets by Langner et al.[1] and for large interactive displays by Reipschlager et al.[48]. The topmost layer in AbVD represents alpha and beta frequencies of F3, the second layer from the top represents alpha and beta frequencies of F4, the third layer represents arousal and the bottom layer represents valence. Each time series graph (F3, F4, valence and arousal) is presented from 0 to 2000 epochs. The dimensions of each AR layer are equal to the size of the tablet display. The QR code can position the AR layers close to display as described in sec [3.2.4].

User interface of AbVD

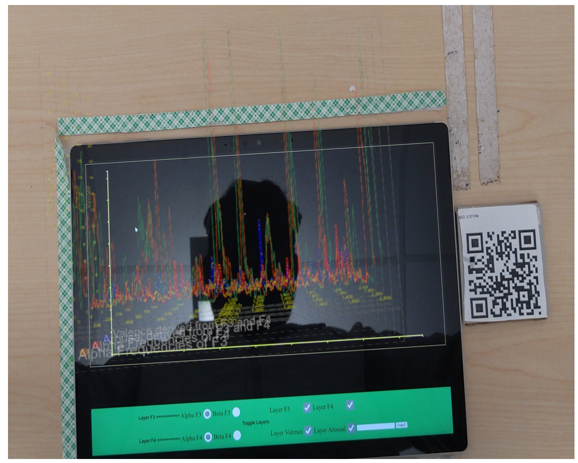
In AbVD four AR layers are controlled by the web application on the tablet comprising of buttons, radio buttons and check boxes as seen in Figure 3.10 (b). The user can toggle on and off individual layers, and switch between displaying the features of alpha and beta in the F3 and F4 layers. We represented each time-series graph in different colors to help participant visually distinguish the graphs. The AbVD interface with all 4 layers is illustrated in Figure 3.10.

Using AbVD

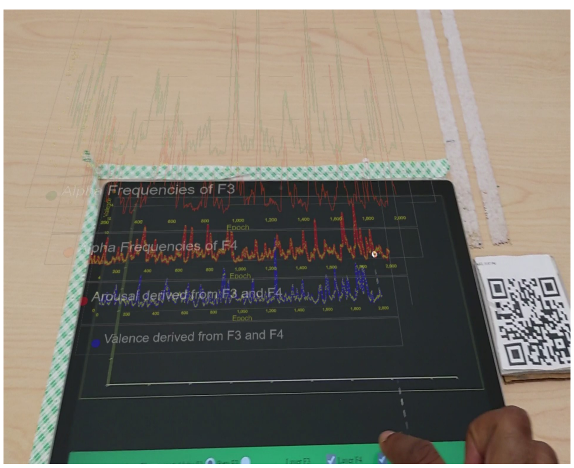
In AbVD, the user can perform data analysis tasks from different resting positions and head orientations. Users can perform data analysis tasks in a seated position by



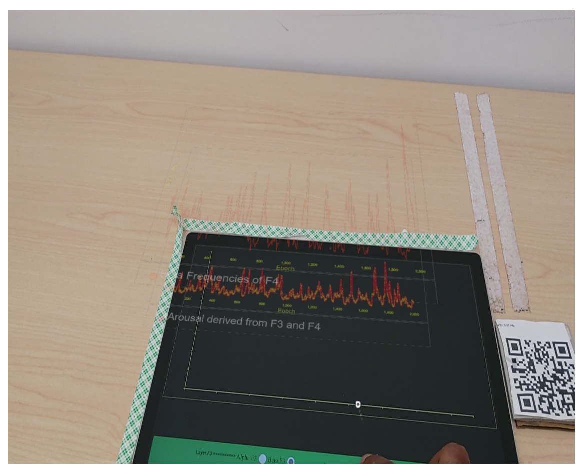
(a) AbVD - Viewing in a seated position



(b) AbVD - Viewing in a standing position



(c) AbVD - User clicks on toggle off



(d) AbVD after toggle off

Figure 3.10: AbVD interface

adjusting their head orientation by leaning back to view AR layers from an angle such that the layers do not overlap, toggling on and off one or more layers, or standing up and looking down to view all layers integrated together. Figure 3.10 also represents viewing angles and toggle operation in AbVD.

3.3.8 ArVD

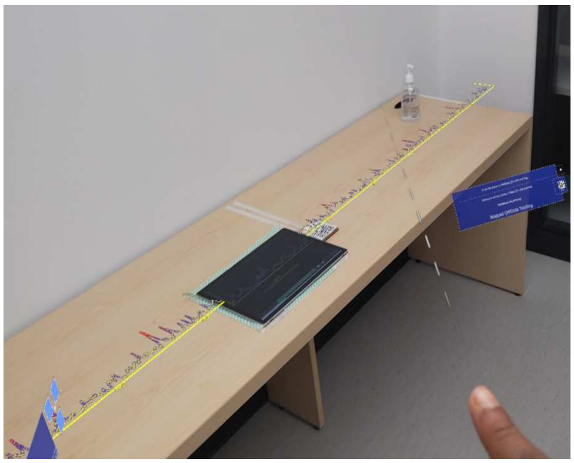
ArVD includes tablet and HMD. AbVD includes one large AR layer that presents time series data on both sides of the tablet display, as shown in Figure 3.11, continuing the time series presented on the tablet. Continuation of data in the context of ArVD means, For example, given a time series data of 7000 epochs, if the portion of the time-series graph on the tablet presents 3000-4000 epochs, on the AR visualization right presents data from 0-2999 and on AR visualization on the left presents 3999-7000 epochs (Figure 3.11(a)). ArVD uses the focus + context view to present the large time series data. Focus+context means keeping a portion of the focus region on the tablet and the remaining portion in AR.

User interface for ArVD

The large time series data is controlled using tablet as shown in Figure 3.11. The user can select between valence and arousal data using the buttons present in the tablet. The small-axis representing the epoch is presented below the time-series graph on the tablet to enable the user to click on a specific epoch which shifts the time-series so that tablet screen is centered on that epoch. The Zoom in and Zoom out button is present in the menu bar to physically expand and shrink the time series data as shown in Figure 3.11 (a),(b),(c),(d). The size, position, and range of the time-series data shown in AR is synchronized with the tablet display such that the data appears to be a single time series graph that extends past the boundaries of the tablet display.

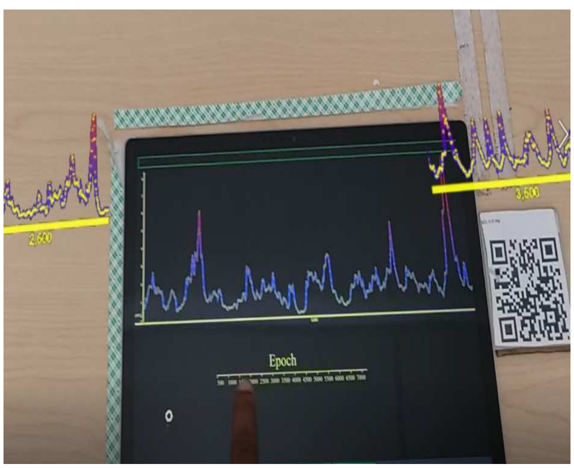
Using ArVD

In ArVD, We can adjust the focus point of the time-series data by clicking on a specific epoch presented on the smaller-axis on the tablet, and the whole time series data will bring nearby data points onto the tablet. We can look at both sides of the AR visualization to identify data points within a specific epoch range and switch the

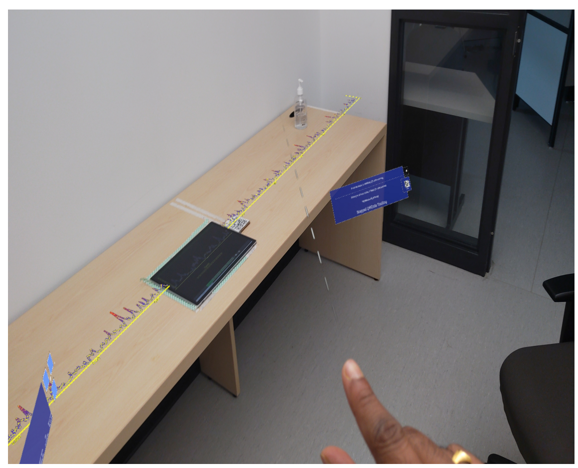


(a) ArVD - When we click zoom in

(b) ArVD - When we click zoom out



(c) ArVD - User clicking on focus point



(d) ArVD - Time series graphs physically adjusts the view

Figure 3.11: ArVD interface

visualization to valence or arousal depending on the task. We can also use shift-left or shift-right to bring nearby data points onto the tablet or zoom out to view more data points on the tablet. The axis labels can be used to locate any point along the entire time-series.

3.3.9 Summary of implementation

To summarize, implementation of AbVD and ArVD started with brainstorming, prototype design, and pilot studies that helped to refine AbVD and ArVD into fully functional interfaces ready for evaluation. We encountered and mitigated some crucial challenges, such as achieving transparency, anchoring AR layers, and making the long-duration time-series data move in sync with the portion of data displayed on the tablet. Building a tablet UI self-explanatory for first-time users is also a key challenge we faced. More information about the challenges, mitigation, and takeaway is presented in the discussion chapter. After successful pilot studies, we evaluated our interface through a controlled within-subject study. The study design for AbVD and ArVD is illustrated in the next chapter.

Chapter 4

Comparative Evaluation of AbVD and ArVD vs. Tablet-Only Interfaces

This chapter focuses on study design for AbVD and ArVD. We present our research questions and hypotheses, recruitment strategy, target population, pre-screening process, tool we used for collecting data, and AbVD and ArVD experiments. A summary of data preparation is also presented in end of this chapter.

4.1 Research questions

We restate our research questions and hypotheses here.

4.1.1 AbVD

Research question 1 (RQ1):-

Can presenting individual time series plots of BCI data on separate horizontal layers in AR enhance comprehension of each plot and of how they are related to each other, compared to presenting them all on a tablet display?.

Hypotheses for RQ1

HA1) Placing time-series data in AR layers above a display leads to faster acquisition of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display.

H0A1) Placing time-series data in AR layers above a display does not lead to faster acquisition of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display.

HA2) Placing time-series data in AR layers above a display leads to more accurate selection of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display.

H0A2) Placing time-series data in AR layers above a display does not lead to more accurate selection of salient data points when the data is oversampled, when compared to presenting all layers on a single physical display.

Task accuracy is a primary indicator for HA2 and HB2. Time taken is a primary indicator for HA1 and HA2. Task load ratings, system usability ratings and custom questionnaire ratings are collected for user experience feedback. We have four task groups in AbVD experiment to test HA1 and HA2. Each belongs to different resting position and viewing angle: **Group 1:-** Seated and toggle, **Group 2:-** Seated and view from an angle, **Group 3:-** Stand up and look through AR layers and **Group 4:-** Use your own approach (Perform tasks in any way with what you have learnt with interface).

4.1.2 ArVD

Research question 2 (RQ2):-

Can extending the boundaries of the tablet screen using AR enhance comprehension of long-duration time series plots of BCI data, compared to zooming and panning on a tablet?.

Hypotheses for RQ2

HB1) Presenting long duration time series data in its entirety by extending a tablet display using AR will permit faster identification of salient data points than when using zoom and pan on a tablet display.

H0B1) Presenting long duration time series data in its entirety by extending a tablet display using AR will not permit faster identification of salient data points than when using zoom and pan on a tablet display.

HB2) Presenting long-duration time series plots of BCI data by extending a tablet display using AR will permit more accurate identification of salient data points than when using zoom and pan on a tablet display.

H0B2) Presenting long-duration time series plots of BCI data by extending a tablet display using AR will not permit more accurate identification of salient data points than when using zoom and pan on a tablet display.

We have two task groups to test HB1 and HB2: **Group 1:-** Using focus+context feature and identify salient data points from entire time-series graph and **Group 2:-** Use your own approach to identify salient data points in time-series graph.

4.2 Study overview

The purpose of this study is to test hypotheses HA1, HA2, HB1 and HB2. We conducted a controlled-within participants study with 48 participants. The evaluation involved two experiments, AbVD and ArVD. Each experiment is compared with similar tasks using tablet-only interface. I was responsible for running AbVD and ArVD study for BCI and another co-researcher was responsible for Space Syntax. Semi-structured interview was conducted by both researchers and they were responsible for asking probing questions relevant to their data (BCI and Space Syntax) to the participants. In data analysis phase, individual researchers who conducted study with BCI and Space Syntax data are responsible for retrieving questionnaire sheets, interaction logs from Surface Pro, gaze data and video recordings from the HoloLens 2. Statistical tests on measures are performed by individual researchers for BCI and Space Syntax. We performed thematic analysis on semi-structured interview data and Inter-rater reliability (IRR) analysis on video observations together as a team. The participants who took part in study are students at Dalhousie University.

We recruited participants with and without prior experience using immersive head-worn displays (AR/VR). The combination of naive and experienced users of HMDs is to mitigate selection bias in our study. As per the recommendation by experts method [63]. We also recruited 5 expert Neuroscience participants from neuroscience school to gain insights about their user experience. We consider our interface generic, and users with any level of experience with BCI or immersive technologies can use our interface, hence during AbVD and ArVD evaluation, we did not target only expert participants from a specific domain. We divided the participants into eight groups in total following counterbalancing. As part of the exclusion criteria, we will excluded the population with color blindness owing to the type of visualizations and tasks. We represented each time-series graph in different colors to help participant visually

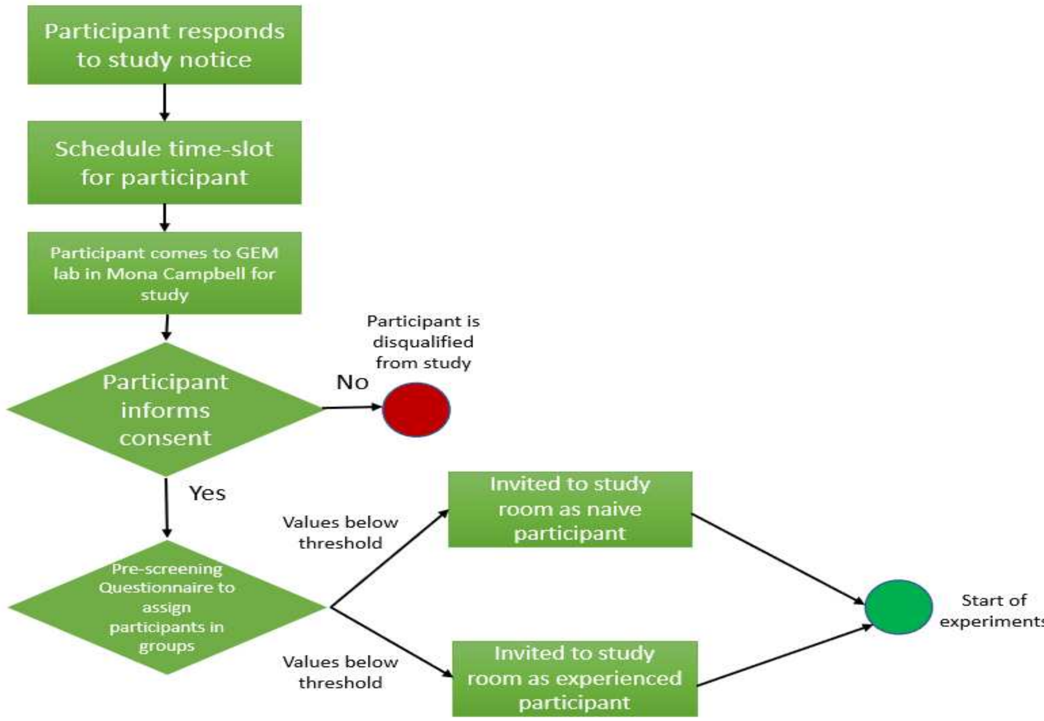


Figure 4.1: Recruitment, consent and pre-screening process

distinguish the graphs. Though visualizations in the AbVD and ArVD require the participants to properly distinguish the graphs and identify data points. During the pilot study, it was observed that it would not be possible for participants having color blindness to perform tasks. The recruitment and pre-screening process is as seen in Figure 4.1

4.2.1 Study notice

We sent a study notice email through Dalhousie internal email server cs-jobs@kil-lsv-2.its.dal.ca and csgrads-bounces@cs.dal.ca. The email draft is attached in Appendix A. When participants expressed their interest through email, I scheduled a time-slot for the study. The participant was scheduled for two time-slots for both AbVD and ArVD experiments.

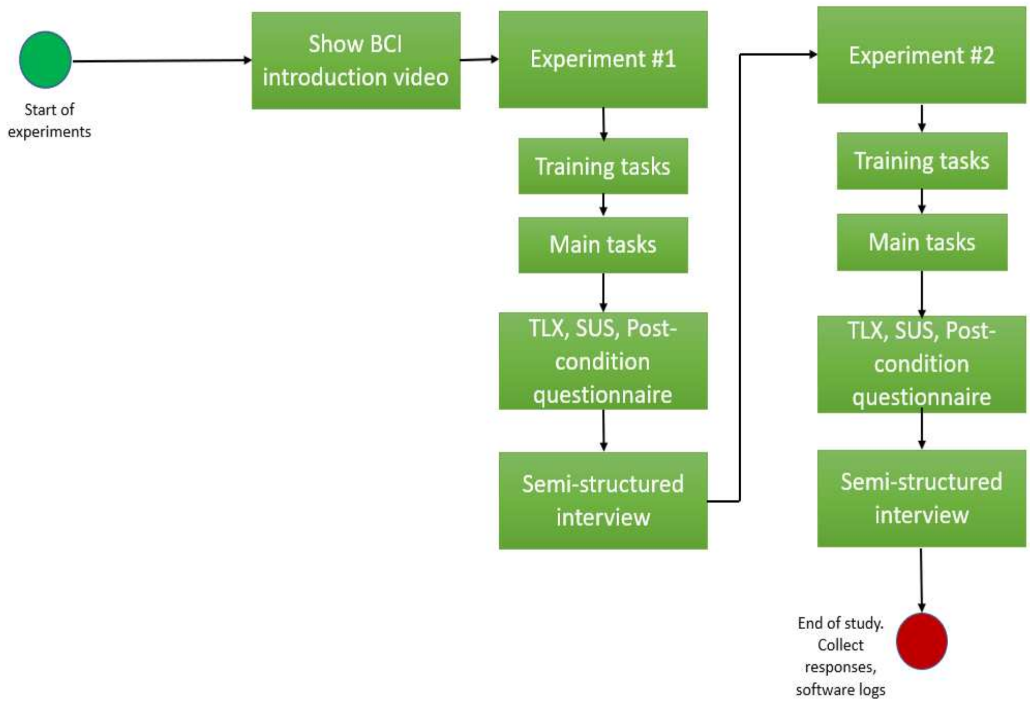


Figure 4.2: AbVD and ArVD Experiments

4.2.2 Initial screening of participants

Participants were asked about their familiarity with using Head-Mounted Displays(HMD) in the pre-screening questionnaire. We have eight groups in total based on the counterbalancing of the task order.

4.2.3 Consent and briefing

The participants informed consent using the consent form(Appendix B) when they arrived at the location. Participants were scheduled for two sessions (maximum 90 minutes each) at the Mona Campbell building 4th floor VR and Graphics Lab. Upon arriving, we gave participants sheets describing the tasks, and one of the investigators verbally explained the purpose of the study and described the tasks to them. The participants were instructed to ask for clarification at any point during the study.

4.2.4 Software tools and devices used

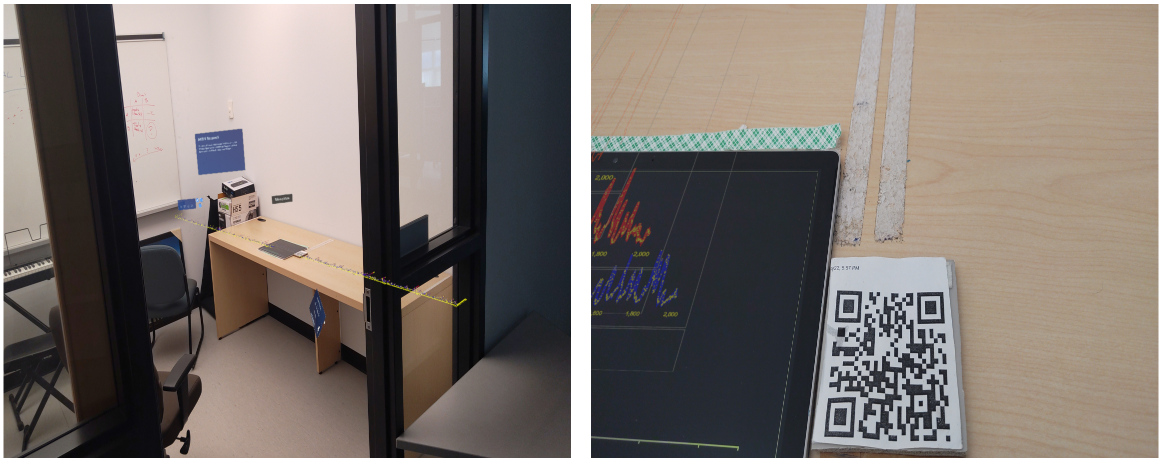
Microsoft HoloLens 2 and Microsoft Surface Book 3 were used by participants in the study. We used built-in video recorder in HoloLens 2 to record the participants' actions during the study. JavaScript logs captured interactions with the tablet. The interviews were recorded through audio recorder software. We used HoloLens companion app [83] to monitor the participants actions during the study. We also recorded participants' gaze data from HoloLens 2.

4.2.5 Setting up the study room

In the study room we marked the location where the tablet was placed with tape. We attached the QR code to the right edge of the tablet and kept the tablet in the marked region on the table. The researcher sat at a distance outside the study room ensured that participants were shown the intended content and interface conditions by monitoring with the remote HoloLens Companion app. Questionnaires were arranged in condition order for each participant. We kept wipes, masks and hand sanitizer in the room in case participants required them. As per COVID protocols, distance between facilitator and participant was maintained and masks were worn by facilitator and researcher. We sanitized HoloLens 2 and Microsoft Surface Pro 3 using wipes before and after the experiment. The study venue is as seen in Figure 4.3(a) and Figure 4.3(b) represents placement of tablet in a marked location on the table.

4.2.6 BCI introduction video

At the outset of the study participants watched an introduction video about BCI that described the features explored in the study. The video provided a short 5 minutes introduction to BCI, EEG signals, devices that capture EEG signals, the OpenVibe platform, representation of EEG signals in OpenVibe, Alpha and Beta frequencies, and features involved in calculating valence and arousal. After showing the video participants were given an opportunity to ask questions before proceeding to the experiments.



(a) Study room with tablet placed on the marked area

(b) Tablet placed in marked area with QR code attached to tablet on right

Figure 4.3: Study venue

4.3 Experiments

Two experiments were conducted as a part of the study, one for AbVD and another for ArVD for BCI data. The experiments included the ArVD and AbVD interfaces I developed for BCI, but also included tasks and interfaces for a different domain (space syntax). I only report on BCI results in this thesis as the space syntax conditions were managed by another student. The flow of experiment is as seen in Figure 4.2

4.3.1 Counterbalancing of experiments

This is a within-subjects study with three factors (Data Domain, Platform, and Interface), each with two levels (BCI and Space Syntax, Tablet+HMD and Tablet Only interface, AbVD and ArVD, respectively). Interface is the outermost factor, and the two levels are treated as separate experiments, each with four conditions–this is because the interactions, visualizations, data, tasks, research questions and hypotheses are different for the AbVD and ArVD interfaces. The Data domain factor is nested within platform, and with counterbalancing this gives the following four orderings per experiment:

Tablet+HMD (Space Syntax, BCI), Tablet(Space Syntax, BCI)
Tablet+HMD (BCI, Space Syntax), Tablet(BCI, Space Syntax)
Tablet(Space Syntax, BCI), Tablet+HMD(Space Syntax, BCI)

Tablet(BCI, Space Syntax), Tablet+HMD(BCI, Space Syntax)

Figure 4.4 represents the counterbalancing order with 8 groups and also presents

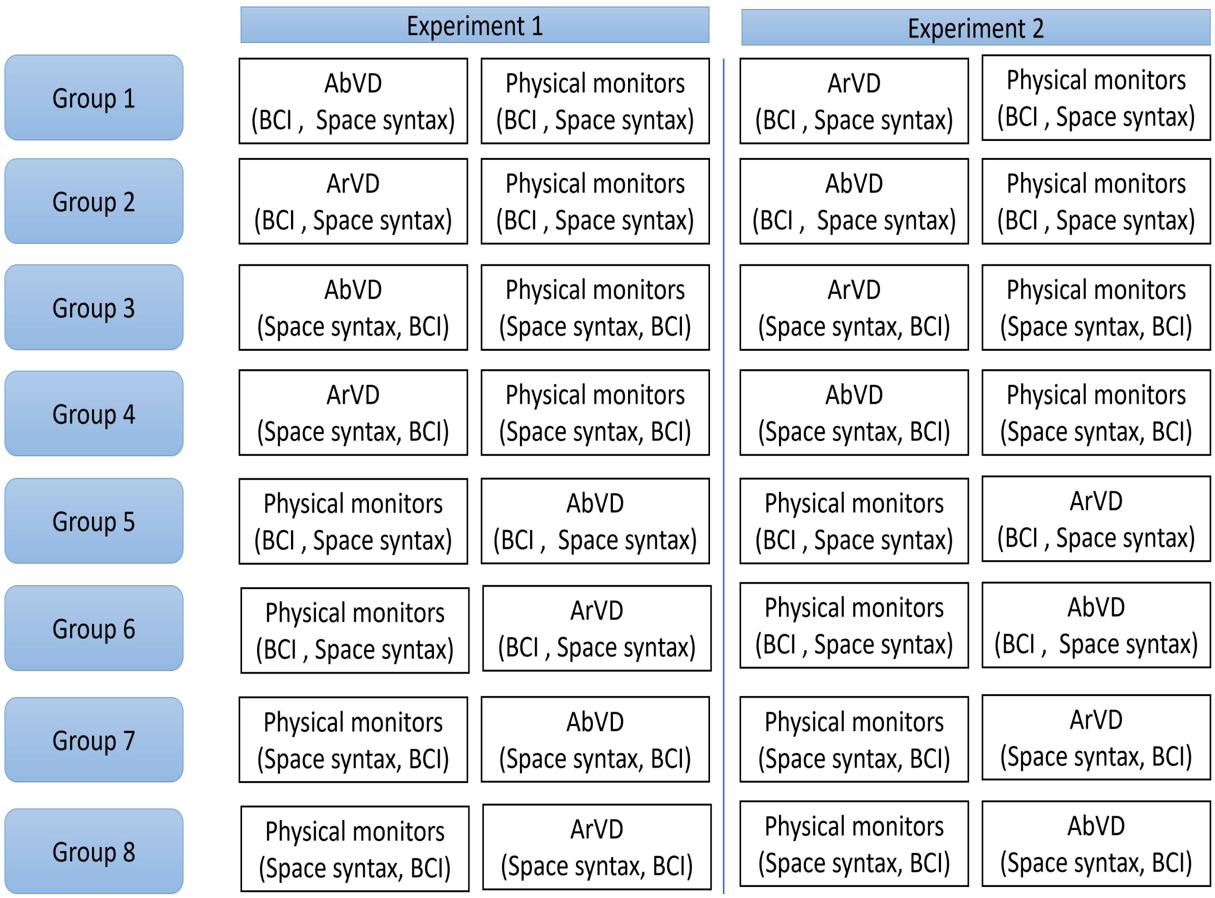


Figure 4.4: Counterbalancing of experiments

counterbalancing as per two data domains (BCI and Space syntax).

4.3.2 Experiment 1: AbVD

In AbVD experiment, we evaluated AbVD against the tablet-only interface. The participants were briefed about the experiment, including the tasks they needed to perform. The participants were asked to explore data and interact with the visualizations presented on the display and in AR layers above the display for BCI. The researcher verbally dictated the tasks step-by-step to the participants, and they carried out operations to complete the tasks described in the task sheet. Participants were asked to "think aloud" as they completed the tasks(Appendix C). Each task set comprised of subset of five tasks, which were completed first and in the same

Activity	Duration(Max)(in mm:ss)
Study overview/review, answer questions	5:00
Describe experiment	5:00
For each condition	x4 (72:00 total)
Complete training tasks	5:00
Complete task set	10:00
Custom questionnaire	3:00
Final questionnaire and semi-structured interview	8:00

Table 4.1: Estimated time for each task in the study

order across all conditions for all participants. These tasks are used to familiarize the participants with the interface, the data domain, and its visualization and to get used to the think-aloud protocol.

After completing the training tasks, the participants performed the main tasks. The main tasks in AbVD were divided into 4 groups based on the head orientation and the resting position. In Group 1, participants were asked to be seated and toggle on or off individual layers to perform the tasks. In Group 2, the participant viewed the data from an angle where the AR layers do not overlap and performed the tasks. In Group 3, participants stood up, looked through all AR layers, and answered the question. In Group 4, the participant can use their own approach to complete the tasks. If a participant expresses concern about not completing a task, they were asked to continue trying until the maximum time is reached.

Once all tasks were completed (or abandoned/timed out) for a given condition, an interface questionnaire(Appendix D), System usability questionnaire(Appendix G) and NASA-TLX questionnaire(Appendix H) were given to the participants. Once the participant finished both tablet and AR task sets, a post-condition questionnaire (Appendix E) were administered. Once the whole experiment for above display was done, a semi-structured interview (Appendix I) was conducted. Table 4.1 presents estimated time for the tasks.

AbVD tablet-only interface

For tablet only baseline condition we asked the participants to perform similar task but with slightly different values in tablet only interface. In tablet-only interface we

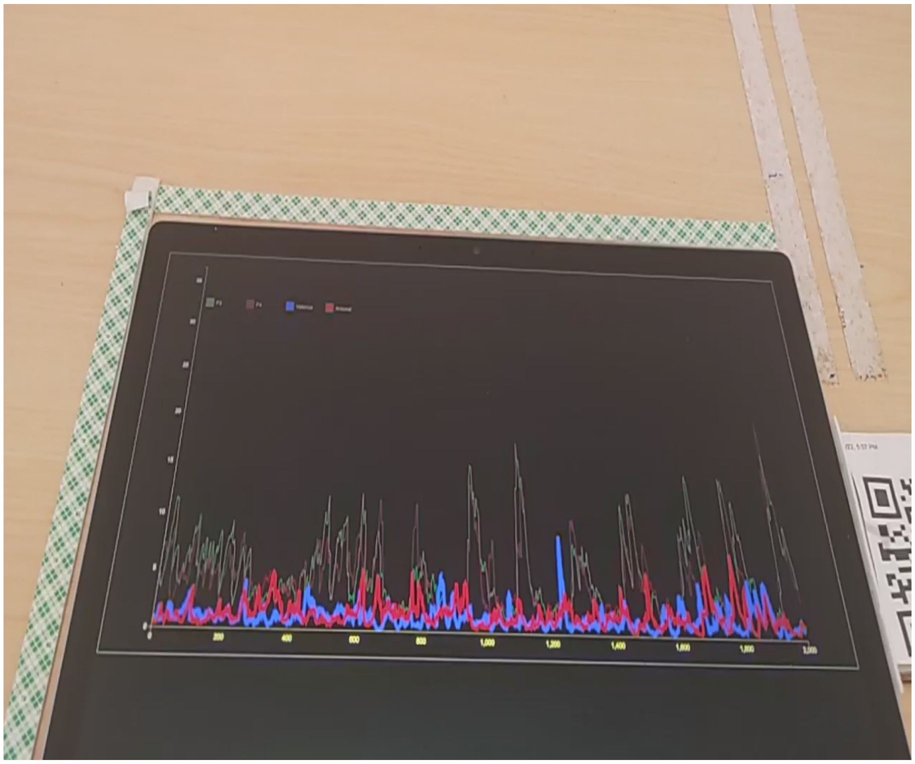


Figure 4.5: Tablet only interface for comparison with AbVD

presented all the four time series graphs together in the tablet. The users can interact with the tablet to switch between the time series graphs and toggle on and off one or more graphs. There are no specific instructions for head orientation or resting positions, the users can perform the tasks normally in the way they use the tablet. Tablet only interface as seen in Figure 4.5.

4.3.3 Experiment 2: Around Display

In ArVD experiment, we evaluated ArVD against tablet only interface. Experiment 2 followed the same format as Experiment 1, differing only in interface and task sets, and required the same amount of time. It is a within-subjects experiment with two factors (Data Domain, Interface), each with two levels (BCI and Space Syntax, Planar and Planar+3D Highlighting, respectively), giving four conditions. The Data Domain factor are nested within Interface, and with counterbalancing this gives the following four orderings:

Planar+3D (SpaceSyntax, BCI), Planar (Space Syntax, BCI)
Planar+3D (BCI, SpaceSyntax), Planar (BCI, Space Syntax)
Planar (SpaceSyntax, BCI), Planar+3D (Space Syntax, BCI)
Planar (BCI, SpaceSyntax), Planar+3D (BCI, Space Syntax)

ArVD experiment had a similar format as AbVD. In the ArVD experiment, we gave participants a set of training tasks to help them familiarize themselves with the interface. Once training tasks were completed, we gave the participants the main tasks. The main tasks had two groups. In Group 1, participants used focus+context to complete the tasks. In Group 2, participants used their own approach to perform the tasks. We provided the participants with an interface questionnaire(Appendix F), System usability questionnaire(Appendix G), and Task load index questionnaire(Appendix H) after each condition. After completion of the ArVD and tablet-only experiment, we gave a post-condition questionnaire(Appendix F) to the participants. Then we conducted a semi-structured interview(Appendix I) with the participants to learn about their feedback.

ArVD tablet-only interface

ArVD was evaluated against the tablet-only interface. The user interface is similar to the ArVD, just without augmented reality. The users had to swipe left and right to navigate through the data. We can use focus points and shift left and shift right functions, in addition, to swipe left and swipe right to navigate the BCI data. There are no specific instructions for head orientation or resting position for the physical monitor condition of the ArVD. Tablet only interface that is used for comparison with ArVD is as presented in Figure 4.6.

4.4 Preparing the data for data analysis

4.4.1 Data collection

Questionnaire data: We gathered responses from consent forms and participant's initial screening data. We collected participants' responses to interface questionnaire,

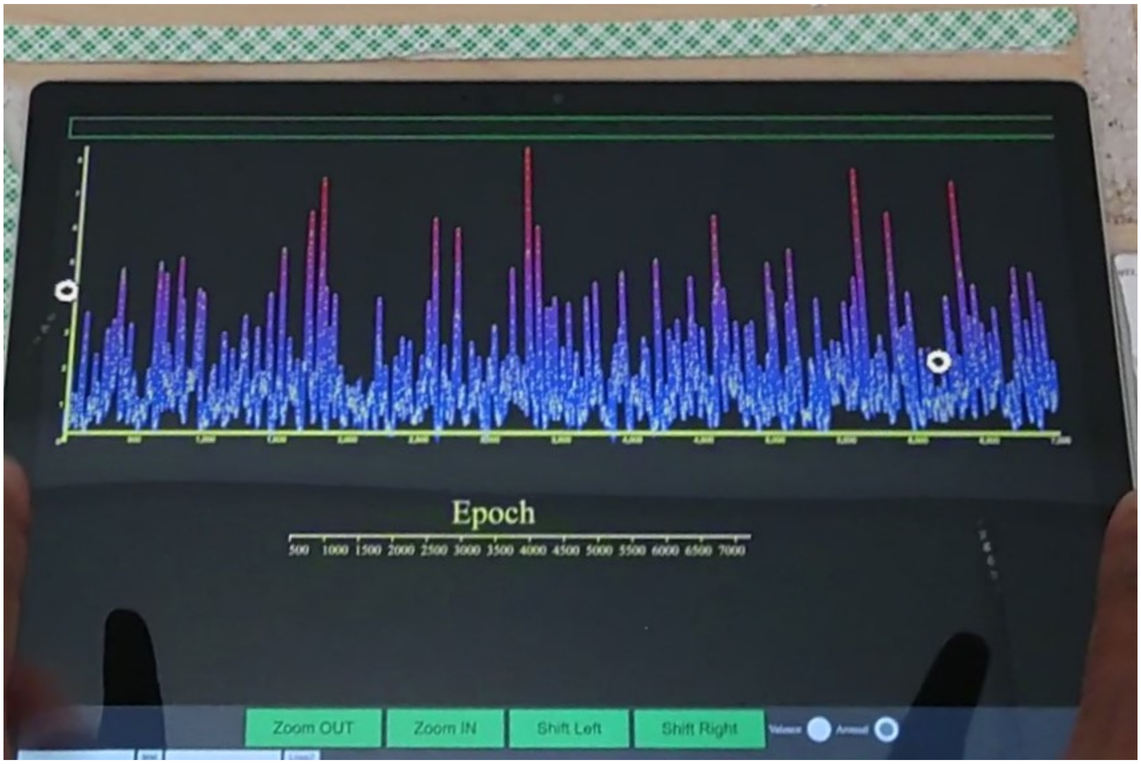


Figure 4.6: Tablet only interface for comparison with ArVD

post-condition questionnaire, SUS and TLX questionnaire. The diversity of participants who took part in the evaluation are presented in Appendix K.

Audio recorder: The audio logs of semi-structured interview was retrieved from the audio-recorder and is later used for transcribing and information collection purposes.

HMD video recorder (HoloLens 2): The HMD has an in-built video recorder which can record the participant's actions and audio.

Software logs: Javascript logs from the tablet application, recorded timestamped data of user interactions in a log file that is later used to check events and its timestamps.

HMD tracking data:the HMD records timestamped head position and orientation, eye gaze, and hand position data. Participants wore HMD for both tablet+AR and tablet only tasks.

4.4.2 Preparing the data

Important measures to answer HA1, HA2, HB1 and HB2 are task accuracy, time taken to complete tasks for each groups. We collected task accuracy and time taken for each group in AbVD and ArVD experiment. We analyzed JavaScript logs, video logs and audio transcripts to obtain accuracy and time-taken for the tasks. For perceived interface feedback, we require system usability scores, task load ratings and custom questionnaire. We collected video and audio logs for both experiments for behavior analysis. The video and audio analysis provided us insights about the participant's experience and categorize their behaviours thematically. We also analyzed JavaScript logs from the tablet to obtain thick descriptions of how each participant completes the task. For qualitative data analysis we analyzed audio transcripts of semi-structured interview data for constructing the feedback thematically.

We structured our during data preparation that portrayed measures of related groups i.e., time taken, accuracy for individual task groups. We wanted to compare our measures for significant difference only for relevant groups that help answering our research questions e.g., Task accuracy for Group 1: Toggle in AbVD and tablet only interface. Structuring the data according to relevant groups helped us to eliminate comparing different groups that are not related and/or did not help answering our research questions. We also applied error correction according to the number of comparisons we performed. Summary of data preparation and analysis plan is described below.

Custom post-condition questionnaire

The post-condition questionnaire contains participant's responses that compared AbVD and ArVD to tablet-only interface. We gathered the responses and complied them in a spreadsheet as seen in Tablet 4.2. The data is ordinal, hence we used Mann-Whitney U test to find significant difference between the responses recorded in Experiment 1: AbVD and tablet only interface and Experiment 2: ArVD and tablet only interface. Epsilon squared test was used for finding effect size. We also applied Bonferroni error correction to mitigate type I error.

A sample from custom questionnaire data recorded in spreadsheet						
Question	Interface	SA	A	N	D	SD
Viewing large time series data	ArVD	18	28	1	1	0
	Tablet	23	22	1	1	0
Panning time-series data	ArVD	27	18	1	0	0
	Tablet	36	11	1	0	0

Table 4.2: Data from custom questionnaire spreadsheet (SA - Strongly agree, A-Agree, N - Neutral, D - Disagree, SD - Strongly disagree)

Data analysis plan for accuracy and time taken

To find significant difference between measures **time taken** and **accuracy** we used **Kruskal-Wallis** for AbVD, ArVD and its respective tablet only interface to test HA1, HA2, HB1 and HB2. In order to validate using Kruskal-Wallis for finding significant difference between the measures we used **Shapiro-Wilk test**. Shapiro-Wilk test indicates if the data distribution is normal. If the distribution is normal then we proceeded to use Kruskal-Wallis otherwise ANOVA can be used for finding significant difference. We did not use ANOVA for any in the results since the data distribution is not normal. We then used Bonferroni correction to mitigate type I error and Epsilon squared test to find effect size.

AbVD To test hypothesis HB1 we use task accuracy as measure. We described about four scenarios or tasks groups where participants performed the tasks in AbVD followed by similar tasks with slightly different values in tablet only interface in the study overview section. We performed hypothesis testing for each task group i.e., Group 1: Seated and toggle tasks, Group 2: Seated and view from an angle tasks, Group 3: stand up and look through the AR layers tasks and Group 4: use your own approach tasks in AbVD experiment. Through statistical tests we compare the task accuracy of each group in AbVD with its counterpart group in tablet only experiment and identified whether tasks performed in AbVD is significantly accurate than the tablet only interface. **For HB1, our dependent variable for each task set (Groups) is task accuracy and independent variable is platform i.e., AbVD and tablet only interface.**

To test hypothesis HA1, we use time taken as measure. Similar to HB1 we have four task groups and we compute time taken to complete the tasks in each group and using statistical tests we identified whether time-taken to complete tasks in AbVD is significantly lower compared to the tasks in tablet only interface. **For HA1, our dependent variable for each task set is time taken and independent variable is platform i.e., AbVD and tablet only interface.**

ArVD To test hypothesis HB2 in ArVD, we used task accuracy as measure. In study overview we described about two task groups where participants performed tasks i.e., focus+context and use your own approach. We computed task accuracy for each group and using statistical tests we identified whether the task accuracy for each group in ArVD is significantly higher than its counterpart groups in the tablet only interface. **For HB2, our dependent variable for each task set is task accuracy and independent variable is platform i.e., ArVD and tablet only interface.**

To test hypothesis HA2, we used time taken as measure for each task groups in ArVD experiment. To identify whether time taken to complete the tasks in ArVD is significantly lower than the similar tasks in tablet only interface we performed statistical tests for significant difference between measures.**For HA2, our dependent variable for each task set is time taken and our independent variable is platform i.e., ArVD and tablet only interface.**

NASA-Task Load Index(TLX)

We collected responses for the perceived task load scores from the TLX questionnaire. We tabulated scores of mental demand, physical demand, temporal demand, performance, effort or frustration data in a spreadsheet as seen in Table 4.3. The scale for each aspect ranges from 0-100. We calculated the overall TLX score for each participant using NASA-TLX spreadsheet[87] that computes overall task load scores from the scores of individual task load factors[86].

The appropriate statistical tests for ordinal data such as Likert scale is debated[119].

Mircioiu et al.[119] stated that the choice of statistical tests for Likert-scale data largely depends on the objective, research question and hypothesis. Our objective is to present cognitive workload for AbVD and tablet only interface from first experiment and ArVD and tablet only interface from second experiment as interface feedback. We visualized individual scores that contribute to task load i.e., mental demand, physical demand, temporal demand, performance, effort and frustration [122, 123]. We mention in our results the significant differences between the scores given by the participants. NASA-TLX is ordinal data hence we used non-parametric test, i.e., Mann-Whitney U test to identify significant difference between the scores, e.g., significant difference between scores of physical demand in AbVD and tablet only interface. Our dependent variables are overall TLX score, physical demand, mental demand, temporal demand, performance, effort and frustration and our independent variable is platform. We used Bonferroni error correction to mitigate type I error and r-statistic to find effect size. We acknowledge the limitations of this approach especially other types of statistical tests that could be used on ordinal data.

A sample from NASA TLX data recorded in spreadsheet				
Task load factor	Response	Participant	Group	Overall score
Mental demand Physical demand Temporal demand Performance Effort Frustration	60 20 0 80 30 0	P1	Group 1	30

Table 4.3: Data from NASA TLX spreadsheet

System Usability Scale(SUS)

Participants' responses to each question in the SUS questionnaire were compiled in a spreadsheet and using SUS scale we calculated the total SUS score. The scores from responses are recorded on the scale of 5-1 i.e, 5-strongly agree, 4-agree, 3-neutral, 2-disagree, 1-strongly disagree. SUS score calculator[85] is used to record the responses and the it contains the formula to calculate the overall SUS score. The SUS formula has three steps. (A) Sum all the responses to odd number questions and subtract by 5, then (B) sum all even number questions and subtract the value from 25, and finally (C) Calculate the sum of A and B and multiply the value by 2.5. The SUS formula is presented in the SUS score column of the spreadsheet as seen in Table 4.4.

In our research we treated we gathered SUS data for perceived usability feedback[124, 125]. In results we visualized system usability scores for experiment 1: AbVD and tablet only interface and experiment 2: ArVD and tablet only interface. We mentioned the grade of SUS overall scores e.g., 76 (Acceptable -'B') [125]. SUS is ordinal data, hence we performed non-parametric tests i.e., Mann-Whitney U test to find significant difference between the scores e.g., significant difference between SUS scores of AbVD and tablet only interface. Our dependent variable is overall SUS score and independent variable is platform. We used r statistic to find effect size.

A sample from SUS calculation recorded in spreadsheet											
Participant	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	SUS Score
P1	2	4	2	4	2	4	2	4	2	4	25
P2	3	3	3	3	3	3	3	3	3	3	60

Table 4.4: SUS calculation spreadsheet

Audio recordings

Our audio data is comprised of audio logs recorded during experiment and semi-structured interview data. The log contains responses of the participants about their overall experience and their feedback about our techniques. We transcribed the audio data to text using Microsoft Cognitive Services[89] and performed thematic analysis (described below) on the data. This method helped us in our qualitative and quantitative findings. Audio logs also helped to make observations on task accuracy based on their verbal responses to tasks and time-stamp data for each the tasks[89].

Once we transcribed the audio logs we performed thematic analysis. Our thematic analysis is motivated from Virginia and Braun[78] that portrays six steps for thematic analysis. However we acknowledge limitations in our approach when compared to [78], since our approach comprised of only four steps and with the audio data we had, we are only able to refine the themes only to certain extent that can distinguish

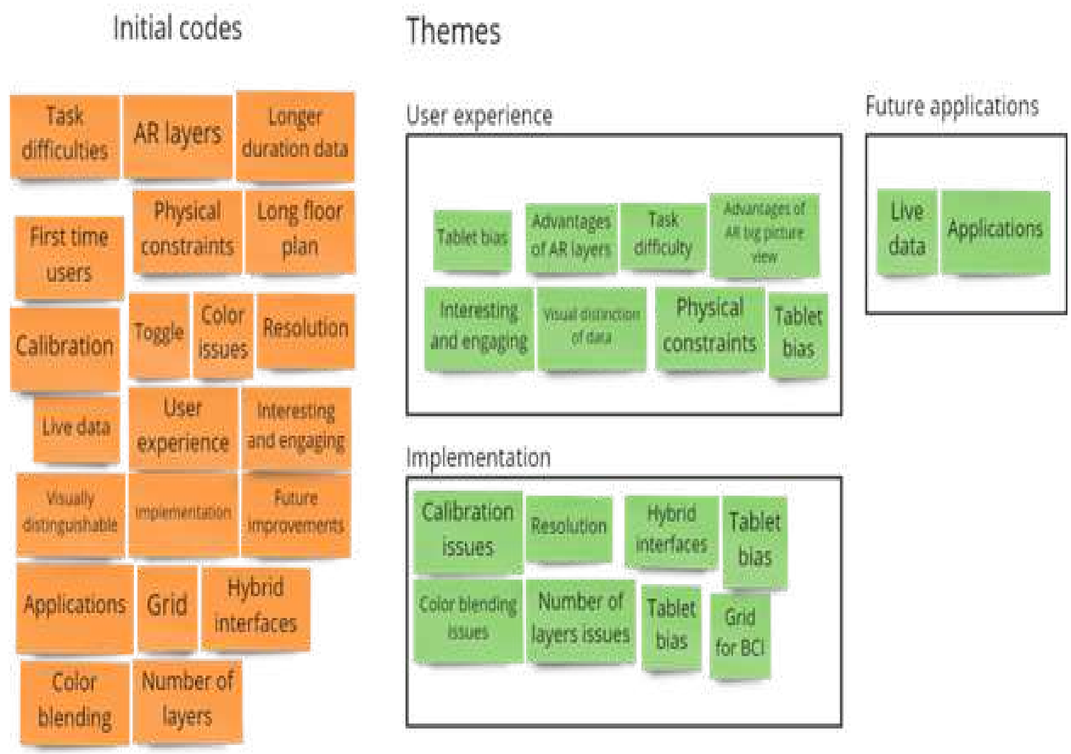


Figure 4.7: Codebook

the category of data. First, utterances during the experiment and interview responses were broken down into data segments such that each segment referred to a single idea, need, action, or object. Second we grouped similar data into bins (e.g., feedback on neck pain, ergonomic issues, head-ache etc.). Third, themes were defined based on the type of data present in the bins (e.g., the theme for neck pain, ergonomic issues, and head-ache is "Physical Constraints"). Fourth, similar themes are connected to a high level theme (e.g., Tablet bias, physical constraints connected to user experience). The themes are derived by three researchers together who took part in the whole process is as seen in Figure 4.7. In our thematic analysis data related to both BCI and space syntax are grouped into bins as seen in affinity diagrams (Figure 4.8-4.17). We only present results from themes relevant to BCI in this research. We performed the whole process in a Miro board tool.

Figure 4.8: Affinity diagram - user experience (Layering advantages)

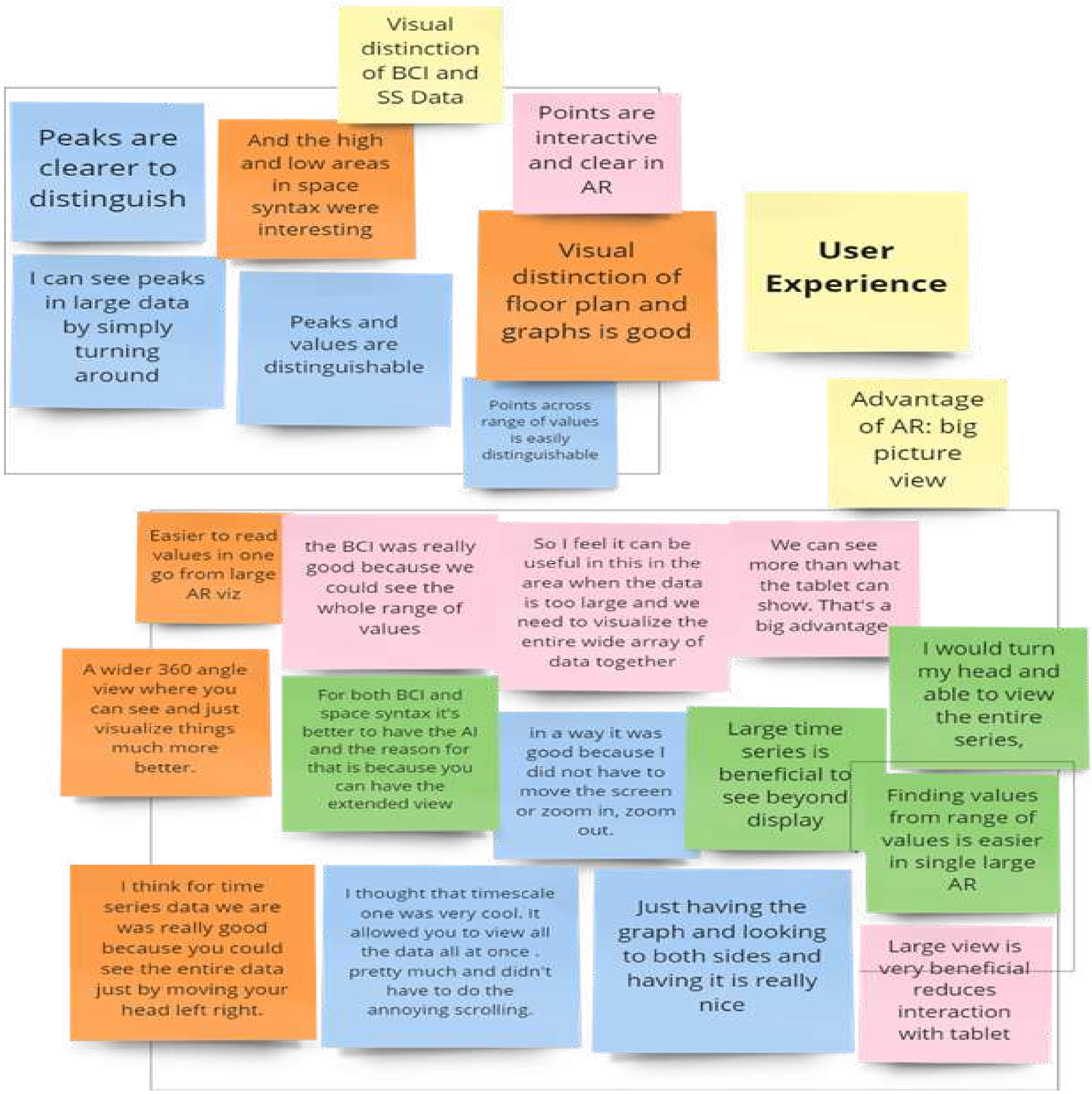


Figure 4.9: Affinity diagram - user experience (Visual distinction and big picture view in AR)

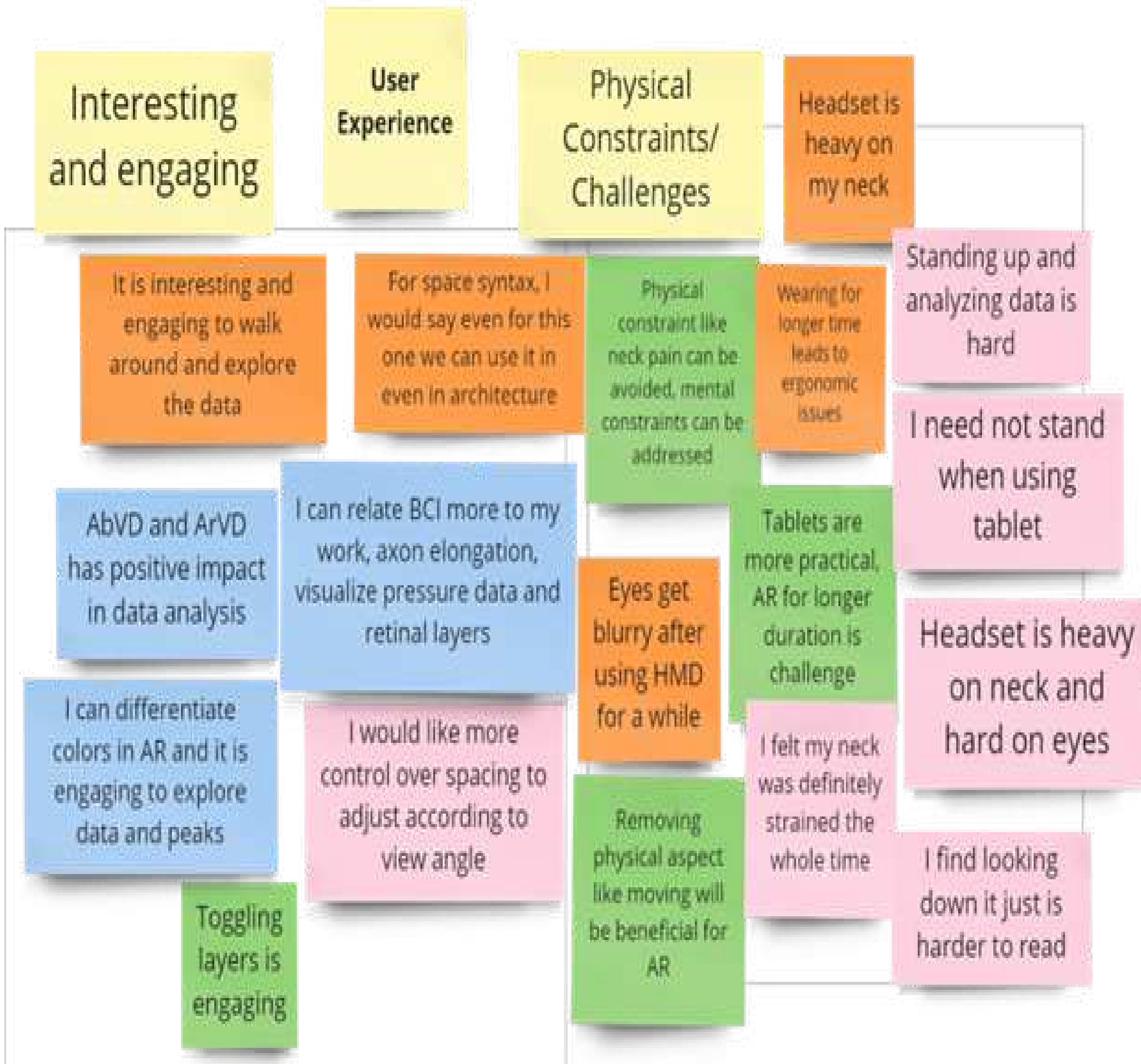


Figure 4.10: Affinity diagram - user experience (Physical constraints and engaging experience)

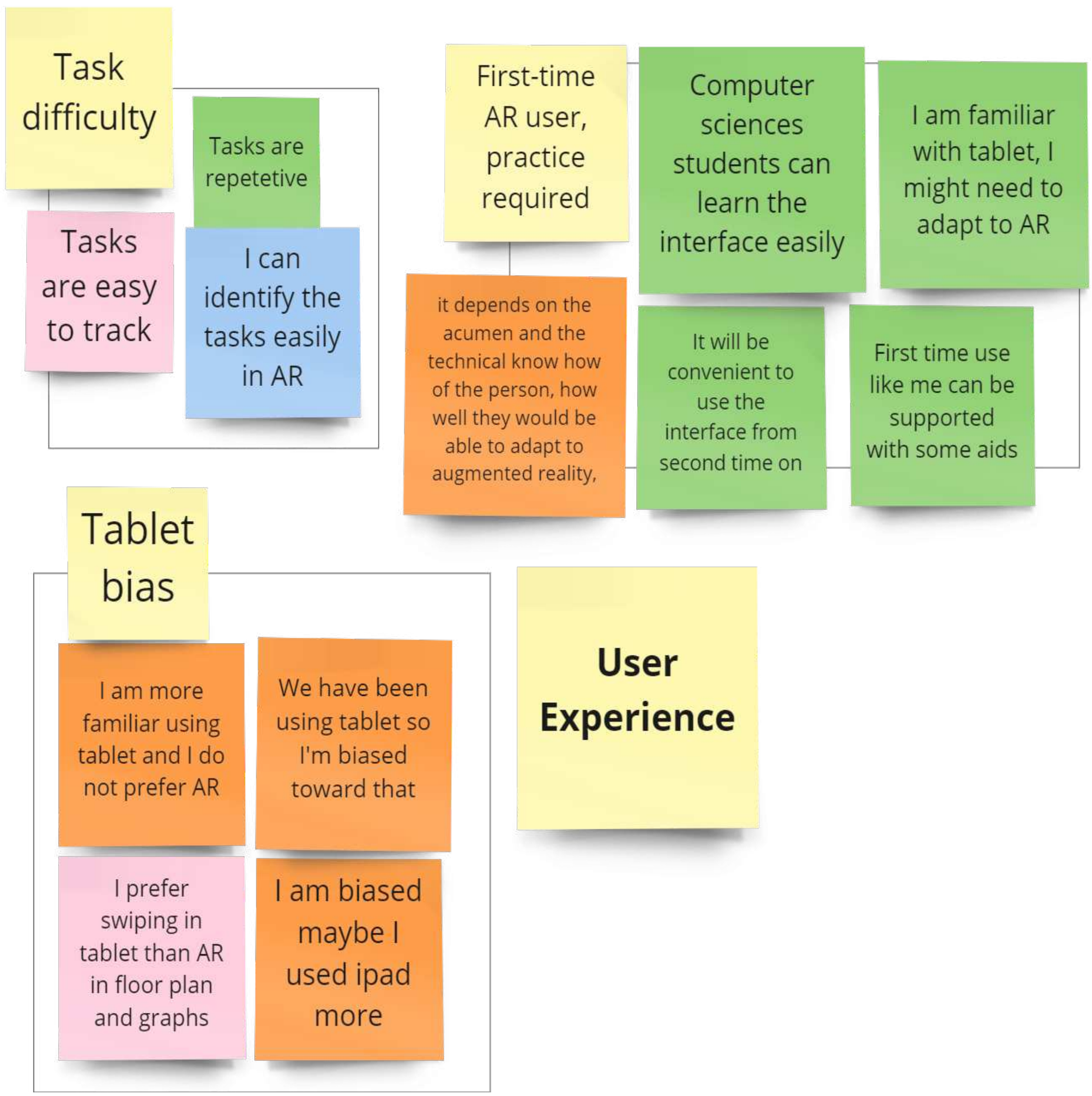


Figure 4.11: Affinity diagram - user experience (Layering advantages)

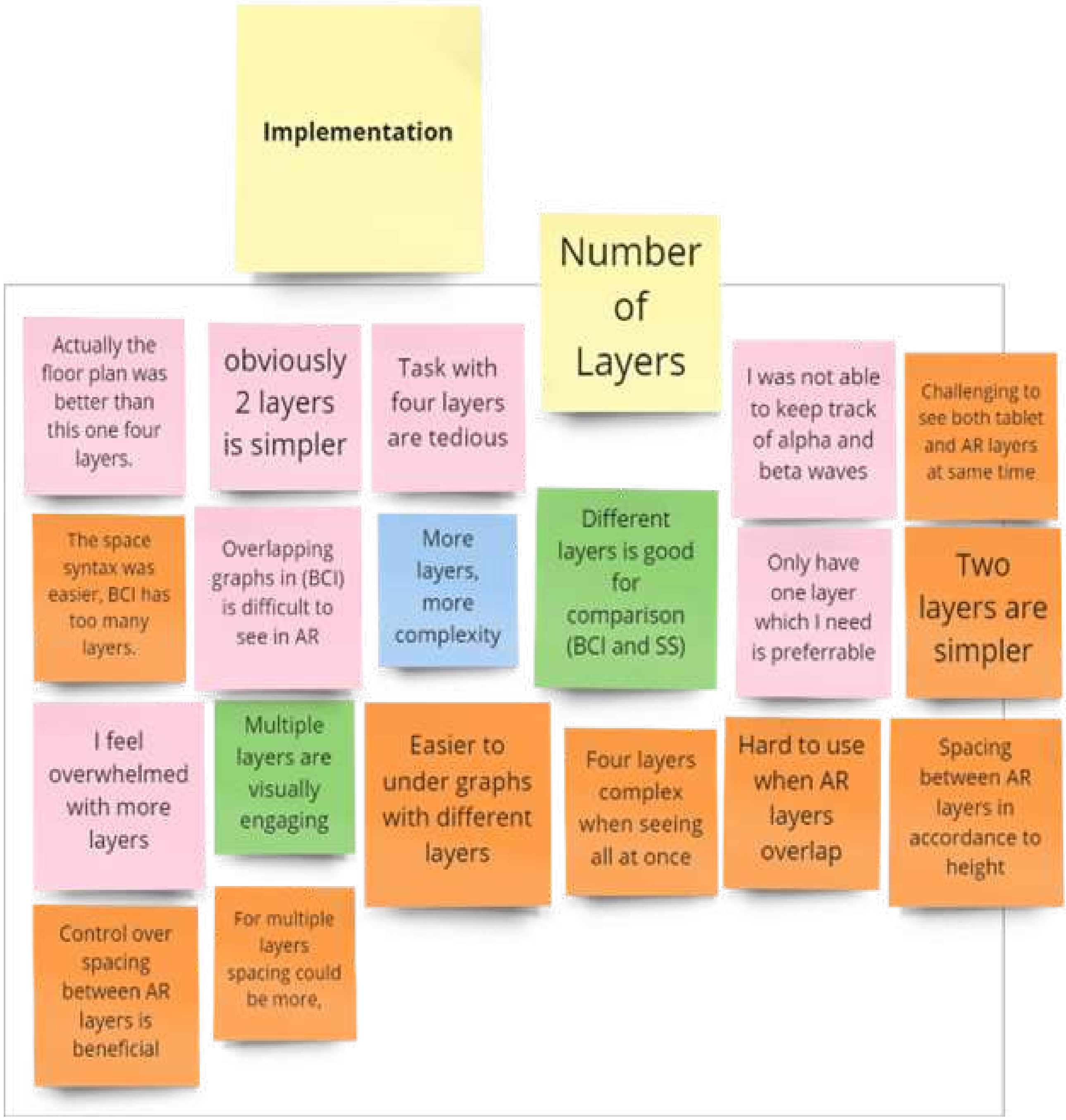


Figure 4.12: Affinity diagram - implementation (Number of layers)

Figure 4.13: Affinity diagram - implementation (Resolution)

Figure 4.14: Affinity diagram - implementation (Toggle and color blending)

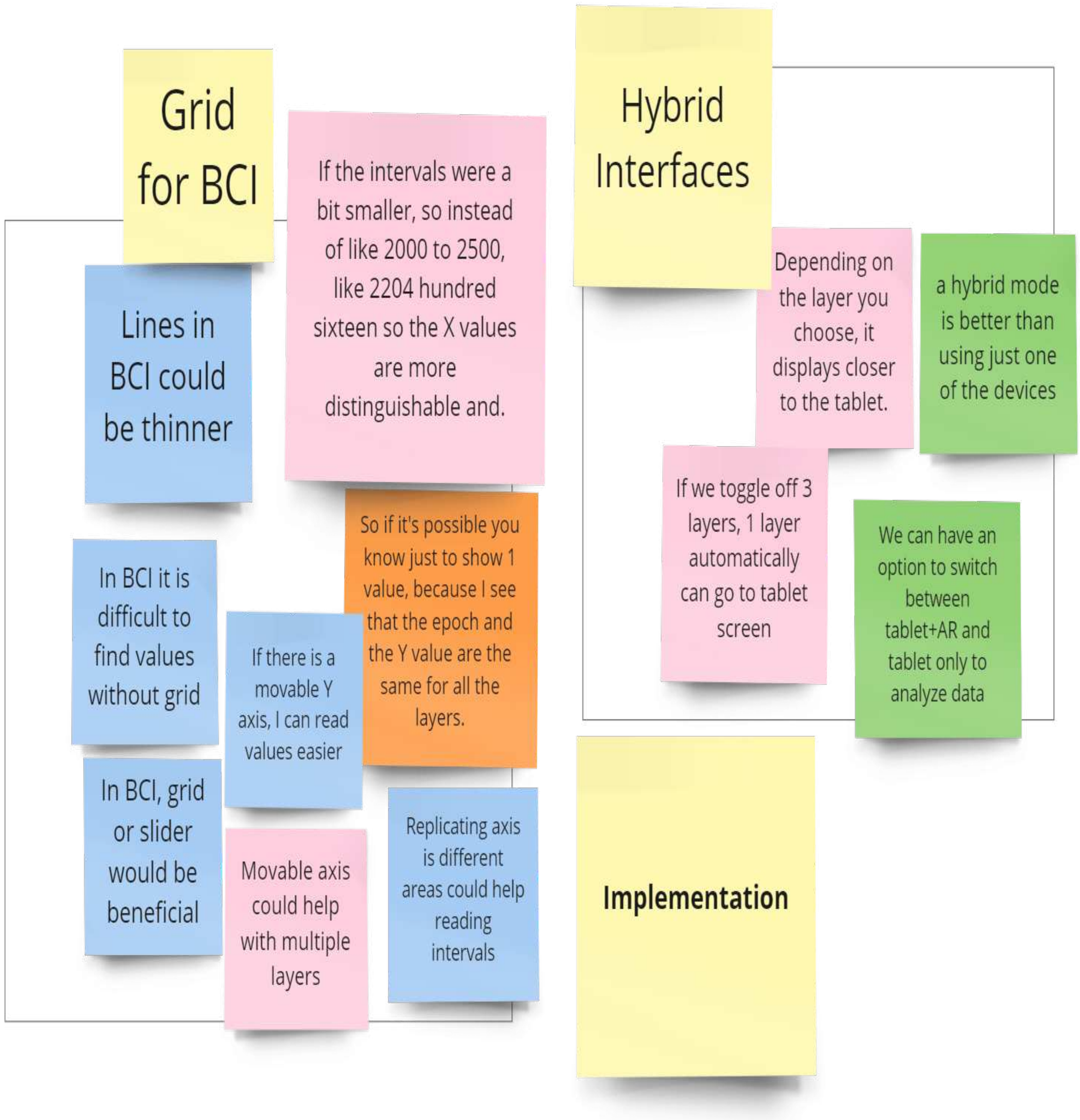


Figure 4.15: Affinity diagram - implementation (Grid and hybrid interface)

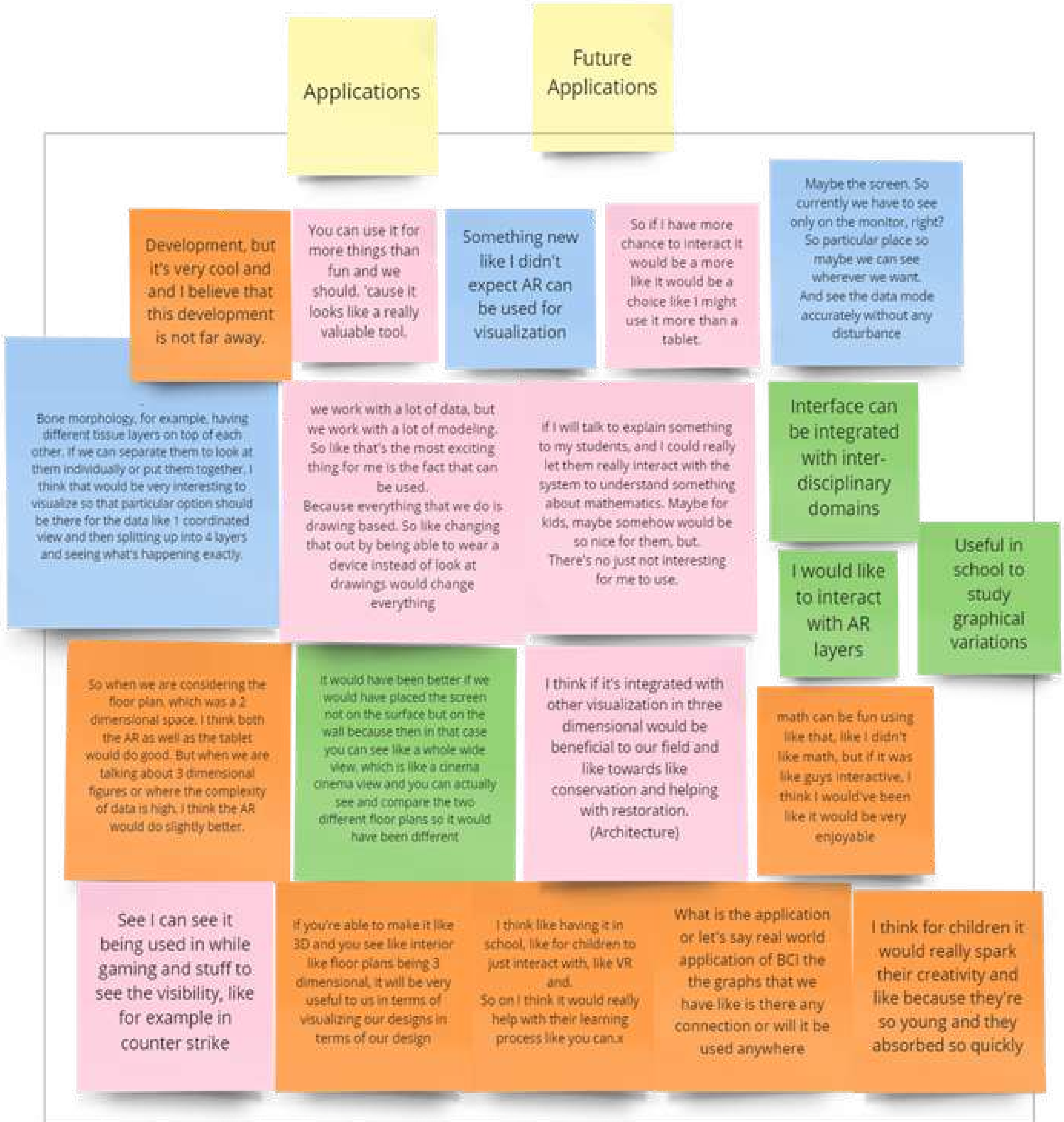


Figure 4.16: Affinity diagram - future applications (Generic applications)

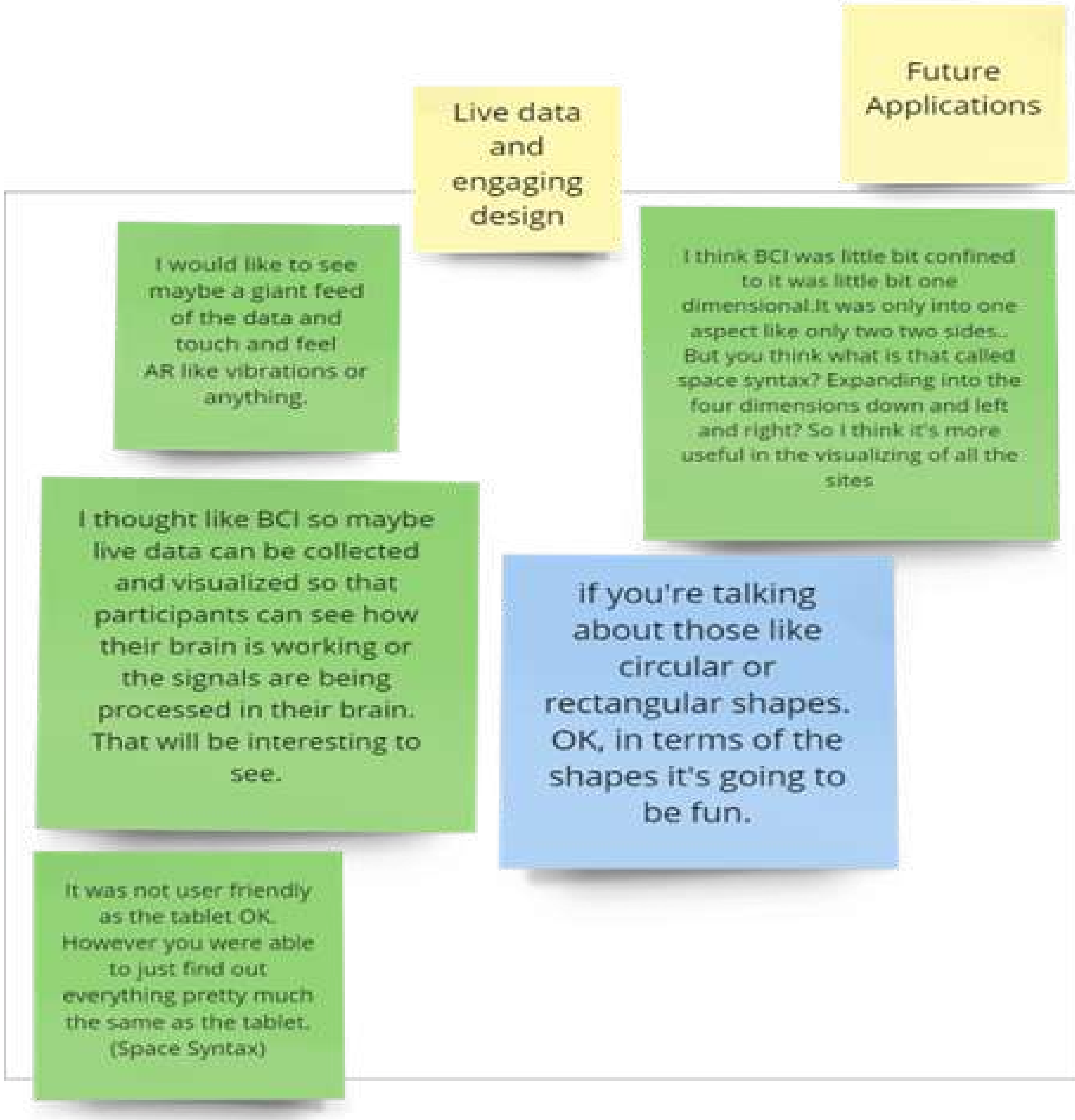


Figure 4.17: Affinity diagram - future applications (Live data)

Video recordings

The video data is collected from the HoloLens 2 for AbVD, ArVD and tablet-only interface. In the video we recorded participants using the tablet+AR and the tablet-only interface performing the tasks. We used inter-rater reliability (IRR) to analyze the video data. The IRR process to analyze the video data involved two researchers analyze the video logs of each participant. After analyzing few video logs and agreeing upon the codes that we can use for further analysis, we started noting the number of each observation of event relating to the code for each video and its time-stamps. When the researchers are done, for video we divided the number of similar codes by each researcher within a given time-frame with total number of codes assigned by each researcher for a participant's video. We continue to do the video analysis until we met acceptable IRR score i.e., above 0.70. Table 4.5 represents the method of IRR calculation performed by both researchers and the codebook for IRR is as seen in Table 4.6.

IRR calculation					
Researcher	Participant	Time	Code	Group	IRR score
1	P1	6:25-6:30 6:44-7:05 7:20-7:35	Participant came close to AR layers Participant came close to AR layers Participant came close to AR layers	2	1
2	P1	6:26-6:32 6:46-7:05 7:20-7:35	Participant came close to AR layers Participant came close to AR layers Participant came close to AR layers	2	1

Table 4.5: IRR calculation

JavaScript logs from the tablet:-

We captured interaction logs from the tablet using JavaScript. Interaction logs captured number of clicks and swipes and recorded each one with a timestamp is as seen

	A	B	C	D
1	Time	EventType	Xpos	Ypos
2	19h:25m:33s:691ms	ToggleValenceOFF	963.5	1037.5
3	19h:25m:34s:283ms	ToggleArousalOFF	1165.5	1041.5
4	19h:25m:34s:283ms	BetaF3	653	954.5
5	19h:25m:34s:283ms	BetaF3	657.5	1033.5
6	19h:26m:55s:996ms	ToggleValenceON	968	1046
7	19h:26m:56s:675ms	ToggleArousalON	1162	1041.5
8	19h:26m:56s:675ms	SwipeLeft:	974	971
9	19h:26m:56s:675ms	SwipeRight:	985	963.5
10	19h:26m:56s:675ms	SwipeRight:	989	961.5

Figure 4.18: Interaction logs from tablet

in Figure 4.18.

Task accuracy:- We calculated task accuracy by examining where the participants clicked in the JavaScript logs from tablet, and reviewing the HoloLens 2 video logs and audio transcripts for a given time-frame. Audio logs are checked to observe participants' verbal responses to the tasks to calculate accuracy. For example, in the task "Click on 1000 epoch from arousal and report its value", we observed the participant's click on arousal button, verbal response of the value and through video logs showing what is displayed.

Time taken to complete the task:- We calculated time taken to complete each task by looking at the time-stamps recorded in interaction logs on when the participant stopped interacting, and adjusted using the HoloLens video logs and audio logs.

IRR codebook		
Code	Group	Interface
Participant clicked on focus point and looked at entire time-series data visualization	1 and 2	ArVD
Participant stood up and moved from location	1 and 2	ArVD
Participant did not use shift left or shift right	1 and 2	ArVD
Participant used zoom in or zoom out to identify data point	2	ArVD
Participant used a combination of shift and focus points	2	ArVD
Participant moved closer to salient data point in seated position to read the value	1 and 2	ArVD
Participant swiped in tablet to identify salient data points	1 and 2	Tablet-ArVD
Participant moved close to AR layer, used finger to match X and Y values	1 and 2	ArVD
Participant came close, adjusted head orientation as per layer and identified the data point	1 and 4	AbVD
Participant used finger to match X and Y value	1, 2, 3 and 4	AbVD
Participant leaned forward closer to AR layer to identify data point	2 and 4	AbVD
Participant stood up and looked down to identify salient data point	3 and 4	AbVD
Participant used toggle feature to isolate layers	1, 2, 3 and 4	AbVD
Kept all 4 layers on when completing the tasks	1, 2, 3 and 4	AbVD
Participant used multiple layers only for comparison tasks	1, 2, 3 and 4	AbVD
Participant used toggle to isolate graphs	1, 2, 3 and 4	Tablet-AbVD
Participant used finger to match X and Y value	1, 2, 3 and 4	Tablet-AbVD
Technical confusion: what is meant by epoch intervals ?	Generic	ArVD
Logical confusion: what is meant by extension of time series data ?	Generic	ArVD

Table 4.6: IRR codebook

Chapter 5

Data Analysis and Results

In this chapter we present data analysis and results. We present results of hypothesis testing using associated measures: task accuracy, time taken. To validate HA and HB, task accuracy and time-taken should return significant results for AbVD and ArVD. User experience is unweighted NASA TLX, System Usability(SUS) and custom questionnaire responses. Qualitative findings on semi-structured interview data and behavioural analysis are presented in this chapter as well. A review of findings in relation to our research questions RQ1 and RQ2 presented at the end of this chapter.

5.1 Study population

Based on the demographic questionnaire, 20 females and 28 males took part in our study and among them 33 participants were familiar with AR/VR. 15 participants stated that they have used an augmented reality application before (e.g., Pokemon Go). The diversity of participants are presented in (Appendix K).

5.2 Statistical data analysis results for AbVD

In this section, we present results for statistical tests on primary measures: task accuracy and time taken to reject H0A. We also present statistical results for perceived task load scores, system usability scores and custom-questionnaire. Qualitative analysis results i.e., semi-structured interview and behavioral analysis results i.e.,video observations and think aloud are presented in later portions of this section. Task accuracy and time taken are as presented in Table 5.1.

5.2.1 Accuracy - Testing hypothesis HA1

Task accuracy and time taken for each group in AbVD experiment portrayed in 5.1. In subsequent sections we present results of statistical tests. Figures 5.1, 5.2, 5.3, 5.4

portrayed visual summary of task accuracy data as box plots.

Above display			
Platform	Task type	Average time taken (MM:SS)	Accuracy
Tablet + AR	Training tasks	03:10	-
	Seated and Toggle	02:40	0.82
	View from an angle	02:20	0.65
	Stand up and look down	02:06	0.68
	Use your own approach	02:02	0.68
Tablet only	Training tasks	02:13	-
	Group 1	02:03	0.82
	Group 2	01:45	0.63
	Group 3	01:37	0.51
	Use your own approach	01:36	0.68

Table 5.1: Average time taken for each tasks in above display

Accuracy for tasks with single layer - seated and Toggle tasks

This is task accuracy for Group 1 in AbVD i.e., Accuracy of the tasks where participants are asked to identify values of alpha, beta, valence and arousal values on each layers in a seated position. Shapiro-Wilk test indicated that the distribution is not normal ($W = 0.93, p < .001$). Hence non-parametric test has to be performed to check statistical significance. The Kruskal-Wallis test is performed to significant difference between AbVD and tablet only interface for seated and toggle tasks. The simple main effect analysis indicated that there was no significant difference in the accuracy for seated and toggle tasks ($\chi^2 = 0.16, p = 0.69, df = 1$) with negligible effect size (ϵ^2=0.002). The mean and standard deviation of AR and tablet are as follows, AR($M = 0.82, SD = 0.14$) and tablet ($M = 0.82, SD = 0.11$). After Bonferroni correction, $\alpha_{new} = 1$. This task set is performed with single layer on and 42 participants used the toggle feature to turn on and off the layers specific to the task.

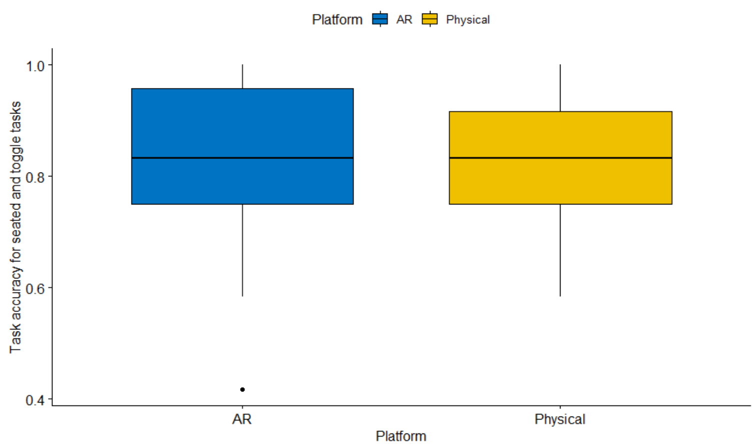


Figure 5.1: Accuracy for seated and toggle tasks

Accuracy for tasks with multiple layers viewed from an angle in seated position

This is Group 2 tasks where the participants are asked to view the AR layers from an angle in tablet+AR tasks and view all the graphs together in tablet-only tasks. The tasks are to find alpha, beta, valence and arousal values at a specific epoch when all the AR layers or graphs are toggled on. Shapiro-Wilk test for normality indicated that the data deviated from normal distribution and non-parametric tests should be performed to check the statistical significance ($W = 0.95, p = 0.002$).The Kruskal-Wallis test showed that there was no significant difference in task accuracy in Group 2 tasks between AbVD and tablet only interface ($\chi^2 = 0.17, p = 0.68, df = 1$) with negligible effect size(ϵ^2=0.002). The overall mean and standard deviation for AR and tablet are as follows, AR ($M = 0.66, SD = 0.19$). tablet ($M = 0.63, SD = 0.17$). After Bonferroni correction, $\alpha_{new} = 1$

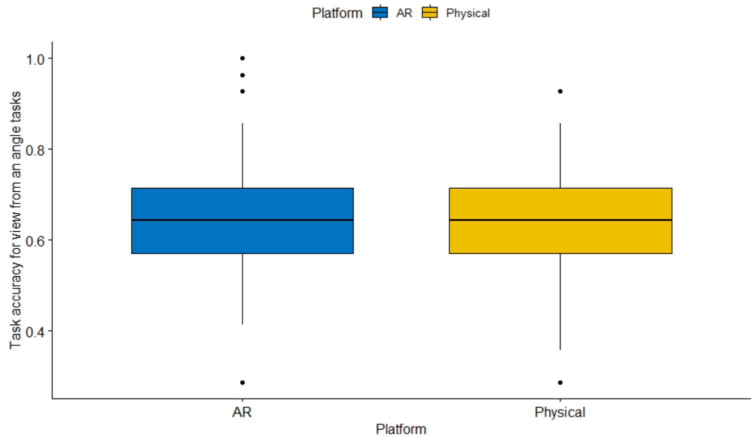


Figure 5.2: Accuracy for view from an angle tasks

Accuracy for tasks with multiple layers and viewed in a standing position - stand up and look down tasks

This is Group 3 tasks where they are asked to stand up and look all the 4 AR layers together as a single visualization. In tablet-only interface, the participants viewed all the graphs together in tablet for the same group. The tasks are to identify alpha, beta, valence and arousal values at a specific epoch. The Shapiro-Wilk test for normality indicated that the distribution is normal hence parametric tests can be used to find statistical significance ($W = 0.97, p = 0.02$).The Kruskal-Wallis test indicated a significant difference in task accuracy for Group 3 tasks between AbVD and tablet only interface ($\chi^2 = 17.738, p < .001, df = 1,$) with relatively strong effect size (ϵ^2=0.19). The mean accuracy of tablet+AR when a participant stood up and analysed the AR layers together was significantly higher than tablet-only for the tasks where the participants analyzed all the time-series graphs overlapping in a single visualization. The mean and standard deviation of AR and tablet are as follows, AR ($M = 0.67, SD = 0.17$). tablet ($M = 0.51, SD = 0.20$). After Bonferroni correction, $\alpha_{new} =< .001$. In this group, 40 participants did not use toggle feature when performing the task, they performed the tasks with all layers on.

Accuracy for finding data points using own approach tasks

We calculated accuracy for Group 4 tasks where the participant can use their own approach to find alpha, beta, valence and arousal values at a specific epoch. The

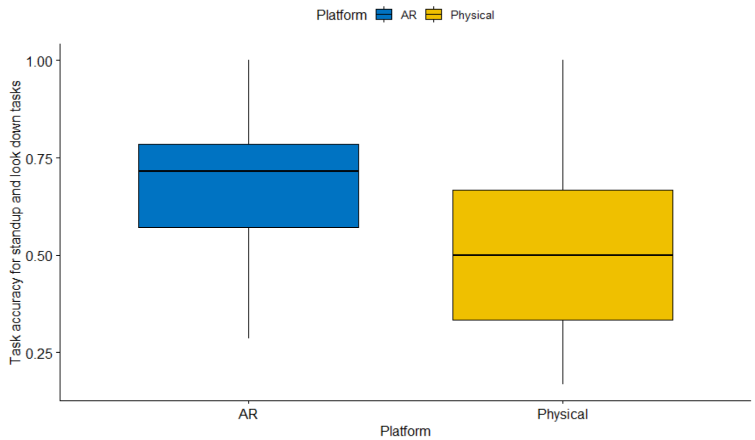


Figure 5.3: Accuracy for Stand up and look down tasks

Shapiro-Wilk test for normal distribution indicated that the distribution is not normal($W = 0.94, p < .001$) and non-parametric test should be performed to find the statistical significance of platform over accuracy. The Kruskal-Wallis did not indicate any significant difference in task accuracy between AbVD and tablet only interface ($\chi^2 = 0.04, p = 0.84, df = 1$) with negligible effect size(ϵ^2 =0.0004). The mean and standard deviation for AR and tablet are as follows, AR ($M = 0.68, SD = 0.20$). tablet ($M = 0.68, SD = 0.23$). After Bonferroni correction, $\alpha_{new} = 1$.

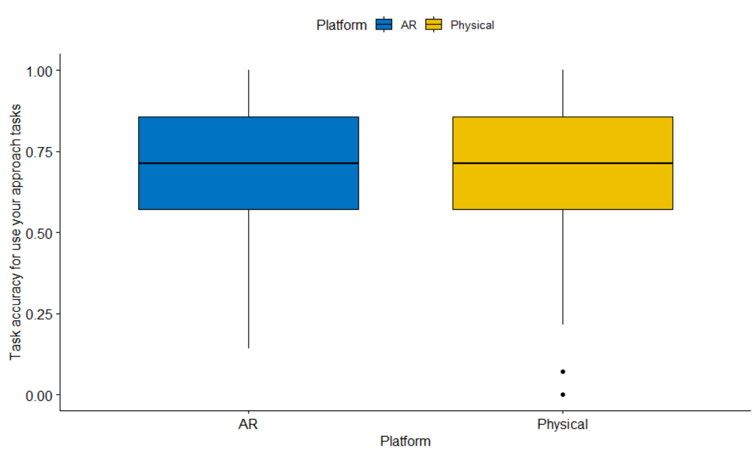


Figure 5.4: Accuracy for use your approach tasks

5.2.2 Time-taken - Testing hypothesis for HA2

In this section, we present statistical results for overall time taken in AbVD and time taken for individual tasks. The visual summary of time taken data is as seen in Figures 5.5, 5.6, 5.7 and 5.8

Time Taken for seated and toggle tasks

For Group 1 tasks, the Shapiro-Wilk test for normality showed that sample is not normally distributed ($W = 0.87, p < .001$). The non-parametric Kruskal-Wallis tests revealed that there was a significant difference in time taken between AbVD and tablet only interface for seated and toggle tasks ($\chi^2 = 9.63, p = 0.002, df = 1$) with moderate effect size (ϵ^2=0.10). The time taken to perform tasks in seated position in tablet+AR is significantly more than tablet-only interface. The mean and standard deviation for AR and tablet are as follows, AR ($M = 2.52, SD = 1.09$). tablet ($M = 1.87, SD = 0.66$). After Bonferroni correction, $\alpha_{new} = 0.008$.

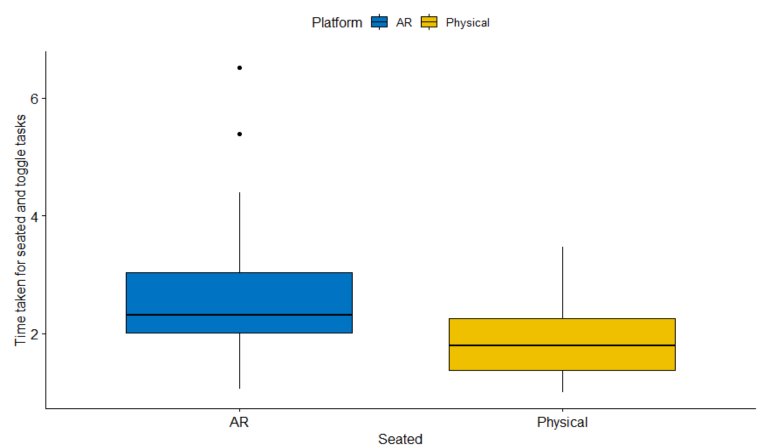


Figure 5.5: Time taken for seated and toggle tasks

Time Taken for view from an angle tasks

For Group 2 tasks, The Shapiro-Wilk test indicated that data is not normally distributed($W = 0.84, p = 7.391e-09$). Non-parametric Kruskal-Wallis tests indicated that time taken in AbVD was significantly higher than tablet only interface, ($\chi^2 = 12.247, p < .001, df = 1$) with moderate effect size (ϵ^2=0.13). Tablet ($M = 1.60, SD = 0.63$), AR ($M = 2.14, SD = 0.92$). After Bonferroni correction, $\alpha_{new} = 0.002$.

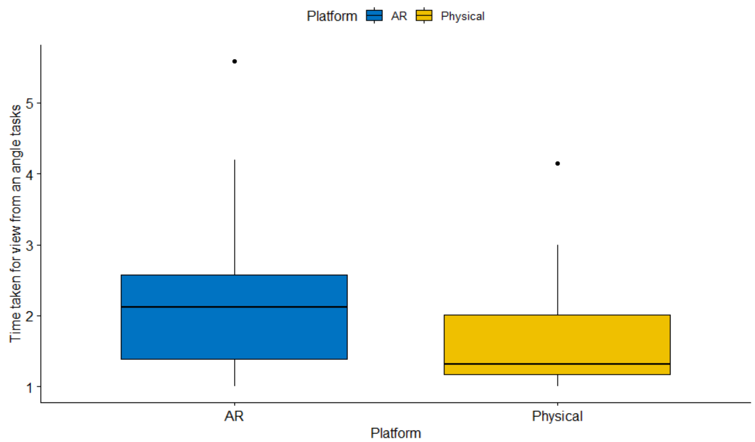


Figure 5.6: Time taken for view from an angle tasks

Time Taken for stand up and look down tasks

For Group 3 tasks, the Shapiro-Wilk test indicated that data is not normally distributed ($W = 0.78, p < .001$). The non-parametric Kruskal-Wallis test indicated that time taken in AbVD is significantly higher than tablet only interface, ($\chi^2 = 13.11, p < .001, df = 1$) with moderate effect size (ϵ^2=0.14). Mean and standard deviation are as follows, AR ($M = 1.90, SD = 0.81$), tablet ($M = 1.45, SD = 0.46$). After Bonferroni correction, $\alpha_{new} = 0.001$.

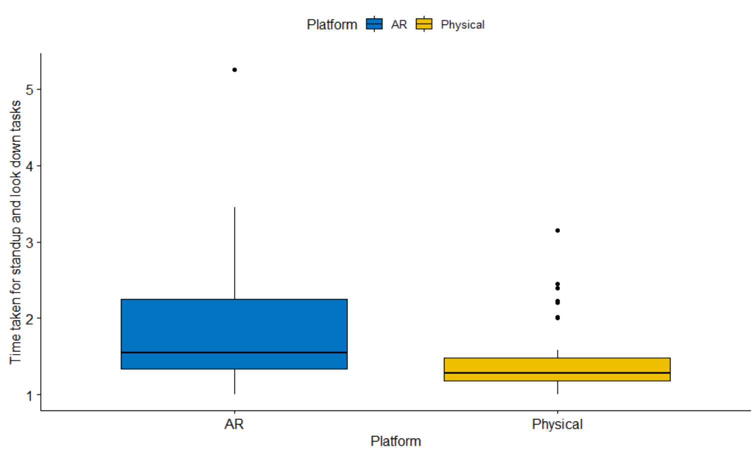


Figure 5.7: Time taken for stand up and look down tasks

Time Taken for use your own approach tasks

For Group 4 tasks, the Shapiro-Wilk test indicated that data is not normally distributed ($W = 0.79, p < .001$). The non-parametric Kruskal-Wallis test revealed that time taken in AbVD is significantly higher than tablet only interface ($\chi^2 = 7.179, p = 0.01 df = 1$) with moderate effect size (ϵ^2=0.14). Mean and standard deviation are as follows AR ($M = 1.87, SD = 0.84$), Tablet ($M = 1.45, SD = 0.50$). After Bonferroni correction, $\alpha_{new} = 0.03$.

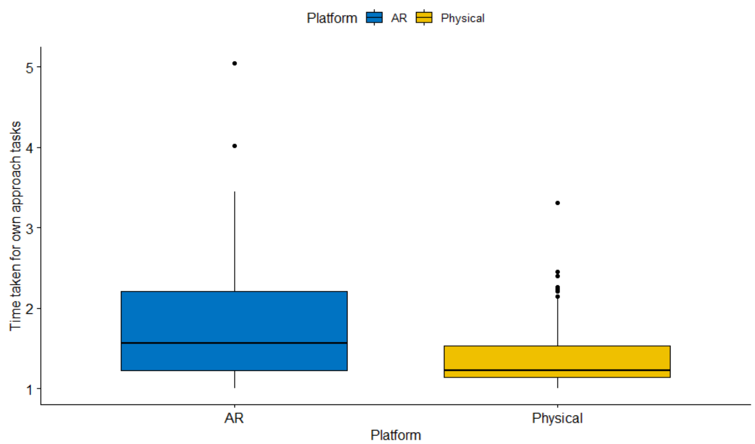


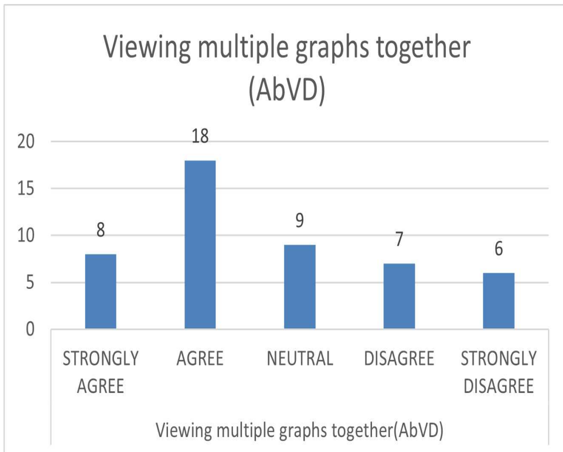
Figure 5.8: Time taken for use your own approach tasks

5.2.3 Custom questionnaire analysis for AbVD

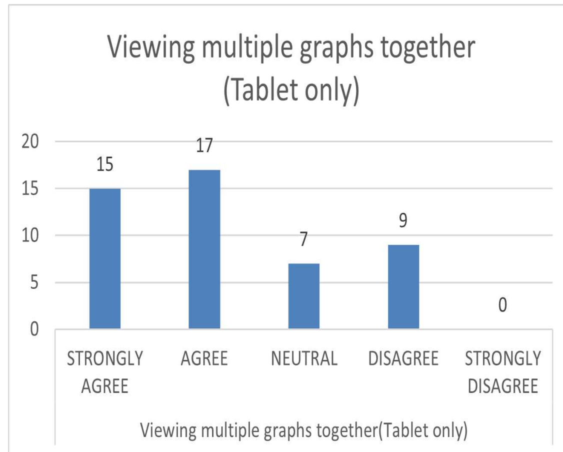
Since the data is ordinal, we used non-parametric Mann-Whitney U test to compute significant difference in responses. We assigned weights ranging from 5 to 1 for the responses: Strongly agree-5, Agree-4, Neutral-3, Disagree-2 and Strongly disagree-1. The responses for questionnaire are presented in Figure 5.9 and Figure 5.10. The statistical results for custom questionnaire are portrayed below in Table 5.2.

5.2.4 NASA TLX

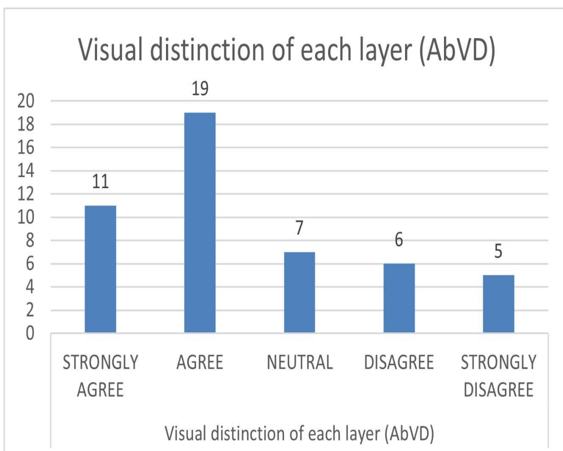
The NASA-TLX scores are unweighted, and we have individual aspects of task load namely mental demand, physical demand, temporal demand, performance, effort, and frustration. During video analysis, we observed that participants had difficulty reading the values of the data points in AR and they adjusted their head orientations



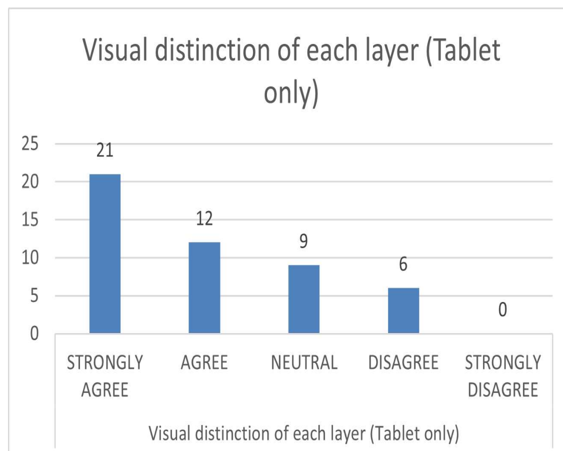
(a)



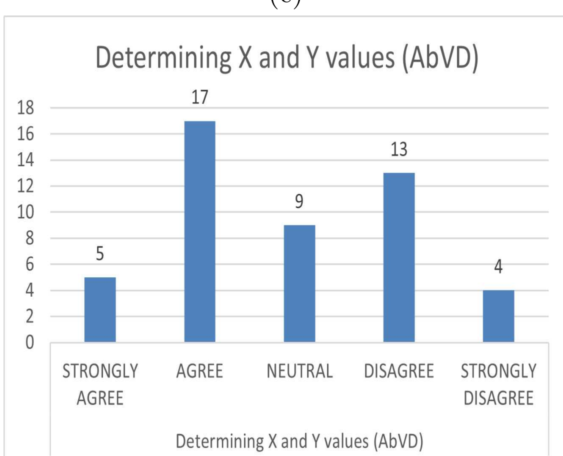
(b)



(c)



(d)



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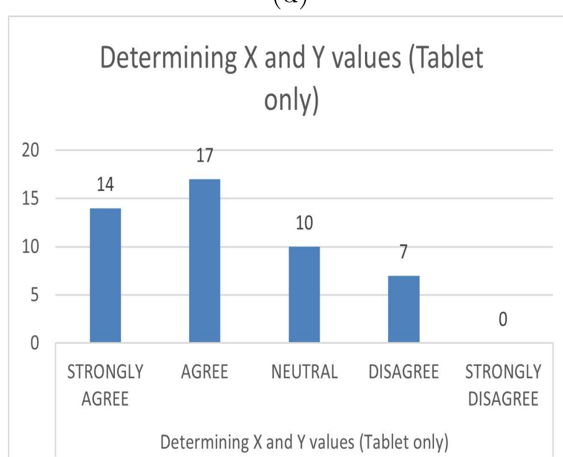
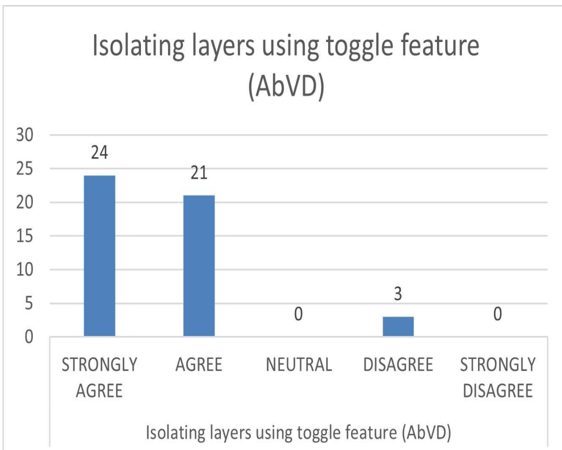
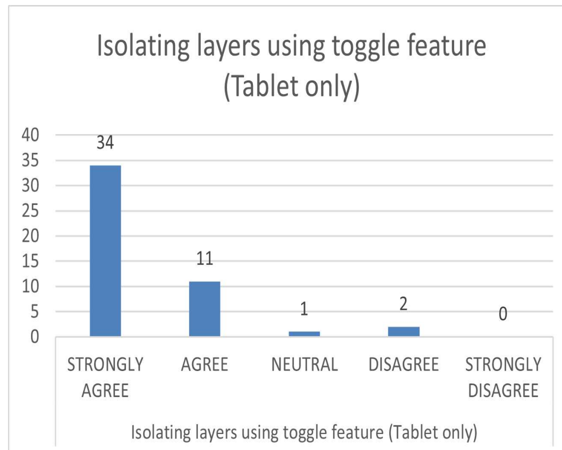


(f)

Figure 5.9: AbVD custom questionnaire



(a)



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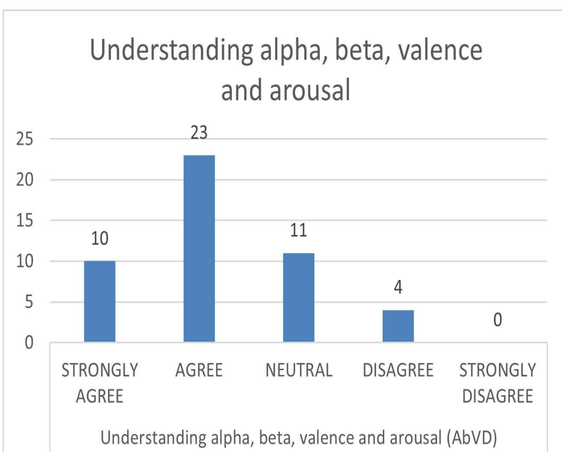

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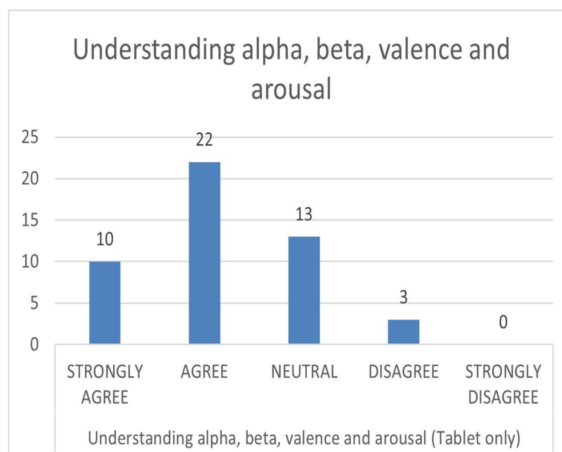


(d)

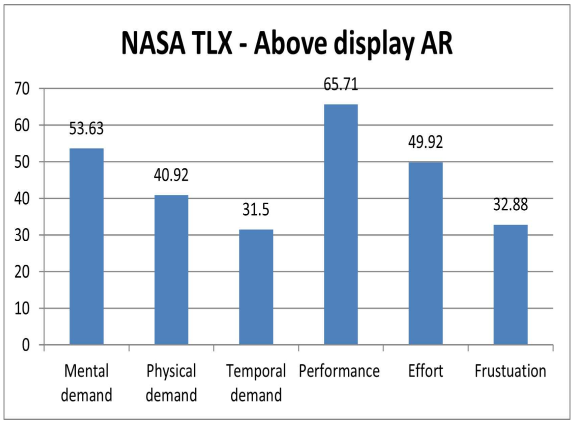
Figure 5.10: AbVD custom questionnaire (Continued)

Statistical analysis on custom questionnaire - AbVD						
Question	W	p	α_{new}	AbVD (Mdn)	Tablet (Mdn)	ϵ^2
Viewing multiple graphs together	868.5	0.03	0.02	4	4	0.04
Visual distinction of layers	903	0.06	0.30	4	4	0.03
Determining X and Y values	792	0.01	0.03	3	4	0.07
Isolating layers using toggle feature	925	0.05	0.27	4.5	5	0.03
Understanding alpha, beta, valence and arousal	1161	0.94	1	4	4	<.001

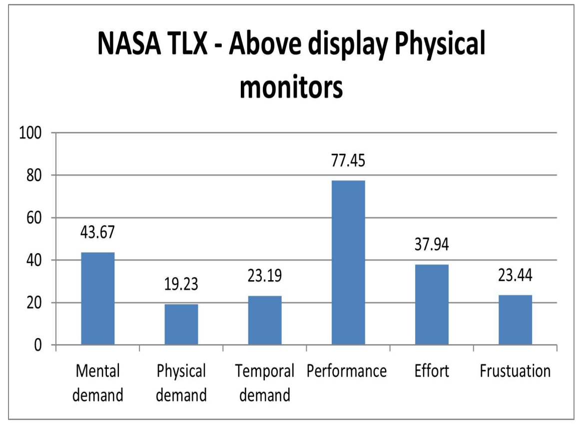
Table 5.2: AbVD Statistical analysis results on custom questionnaire responses

close to the data point to read its value. However, the participants did not felt the need to change their head orientation or resting position in tablet-only tasks. The participants looked into the tablet, interacted with the interface, and answered the questions. Task load factors and overall NASA TLX score for AbVD and tablet only interface is as seen in Figure 5.11. Data distribution of individual task load factors in AbVD and tablet only interface are visualized in Figure 5.12.

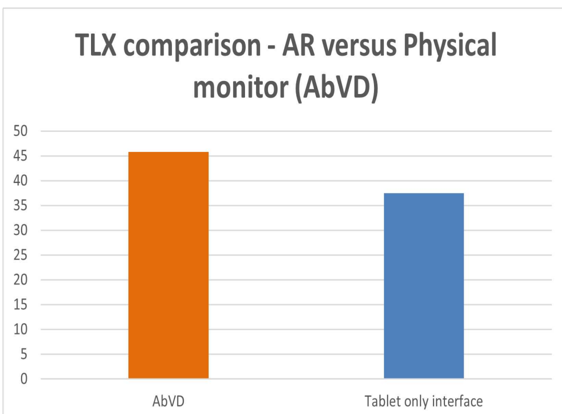
Mann-Whitney U test indicated that there is a significant difference between the overall NASA TLX score of AbVD and tablet only interface ($W = 1467, p = 0.02$) with small effect size ($r = 0.23$). Mann-Whitney U test also indicated that AbVD has significantly higher perceived physical demand with moderate effect and effort



(a) AbVD



(b) Tablet only interface



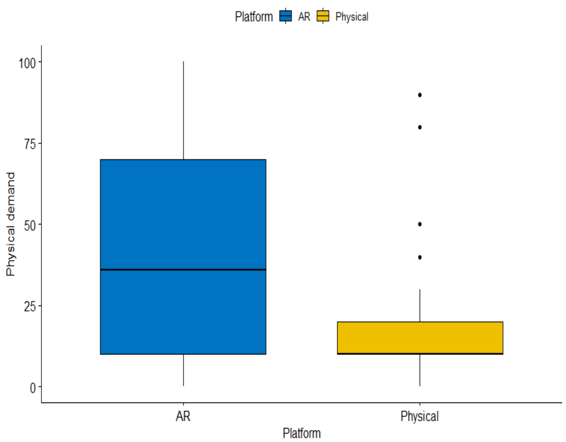
(c) Task load comparison

Figure 5.11: AbVD NASA-TLX

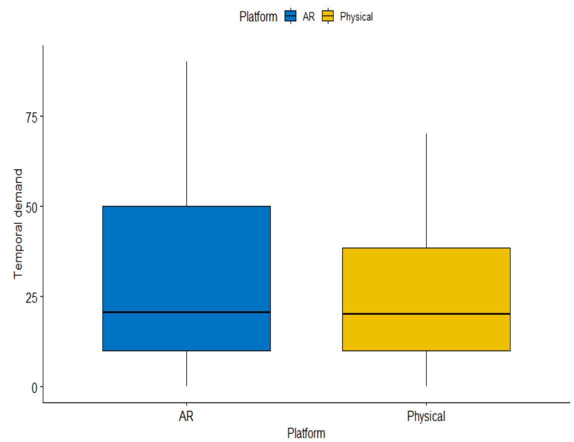
with low effect size. Our effect sizes are as per r-statistic. Tablets have significantly higher performance scores with low effect size. Statistical results of Median, p-value, effect size(r) and sum of the ranks(W) are portrayed in Table 5.3.

5.2.5 System Usability Scores(SUS)

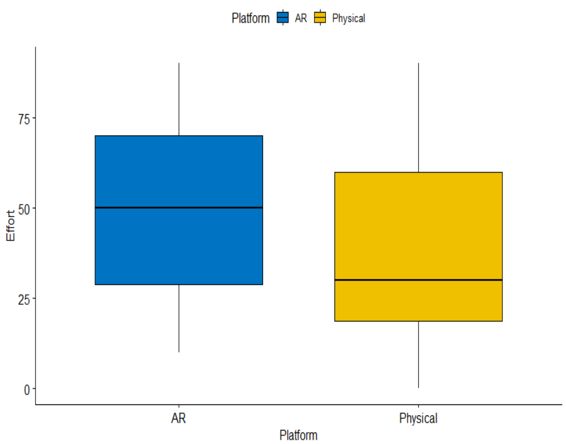
The self-reported system usability scores for AbVD is 66 which points to marginal rating of 'C' , and tablet-only interface is 76 which points to acceptable rating of 'B'. During the interviews and prior screening of participants, they mentioned that they had not used a hybrid interface before. They also expressed that they are more familiar with tablet computers. Eleven participants reported in their responses that they might need a help of a technical person to use the interface, which outlines their non-familiarity with the interface. Thirty-six participants reported that the system is



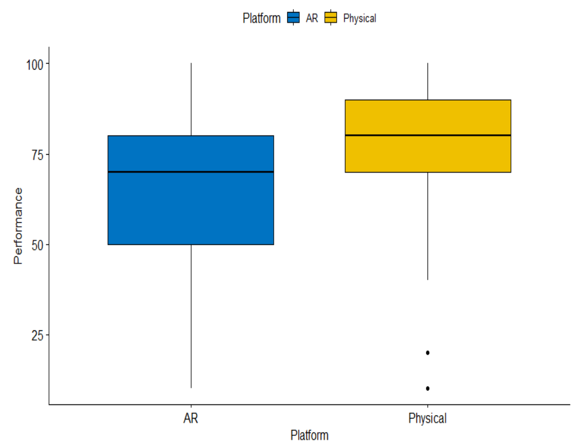
(a) Physical demand



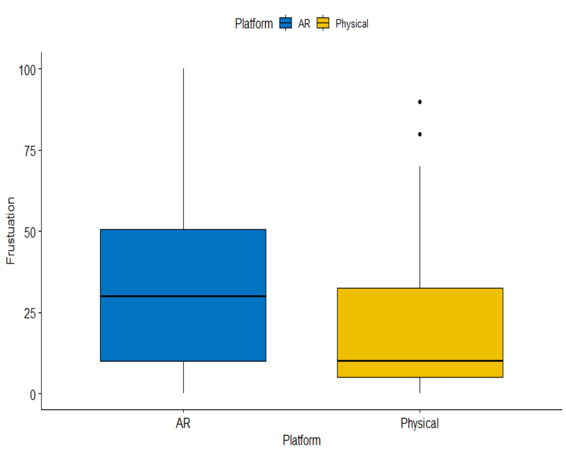
(b) Temporal demand



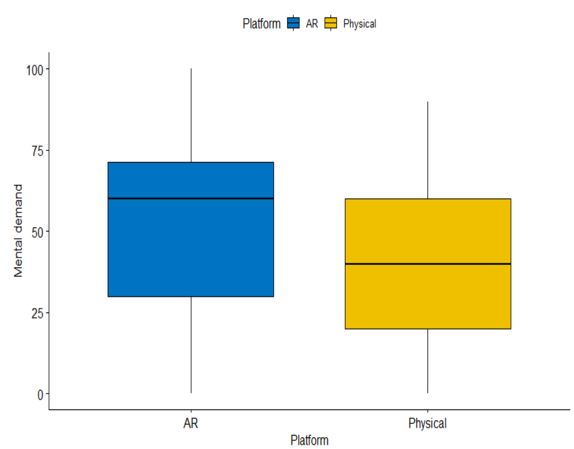
(c) Effort



(d) Performance



(e) Frustration



(f) Mental demand

Figure 5.12: AbVD - Comparison of TLX factors

Statistical analysis on perceived task load						
Task load	W	p	AbVD (Mdn)	Tablet (Mdn)	Effect size (r)	α_{new}
Mental demand	1403	0.07	60	40	0.18	0.42
Physical demand	1639	<.001	36	10	0.37	0.01
Temporal demand	1350	0.15	20.5	20	0.15	0.9
Performance	756	0.003	70	80	0.29	0.02
Effort	1459	0.02	50	30	0.23	0.12
Frustration	1367	0.11	30	10	0.16	0.66

Table 5.3: NASA TLX - Perceived task load summary for AbVD

easy to use, and 39 participants found that various system functions are easy to use. 28 participants also expressed that they felt very confident using it. The self-reported system usability scores of physical monitors are higher at 76. SUS scores of AbVD and tablet only interface is as seen in Figure 5.13.

The Mann-Whitney U test on the system usability ratings showed that there is a significant difference between scores of AbVD and tablets ($W = 748, p = 0.003$) with negligible effect size ($r = -0.03$). The system usability ratings of tablet-only interface ($Mdn = 75$) is significantly higher than the tablet+AR interface ($Mdn = 67$). There is no change to p-value after Bonferroni since there is no multiple comparisons for system usability scores.

5.3 Behaviour analysis for AbVD

5.3.1 Video observations

We observed how the participants performed each set of tasks in tablet and in augmented reality from the video logs. We looked into specific patterns of behaviour by

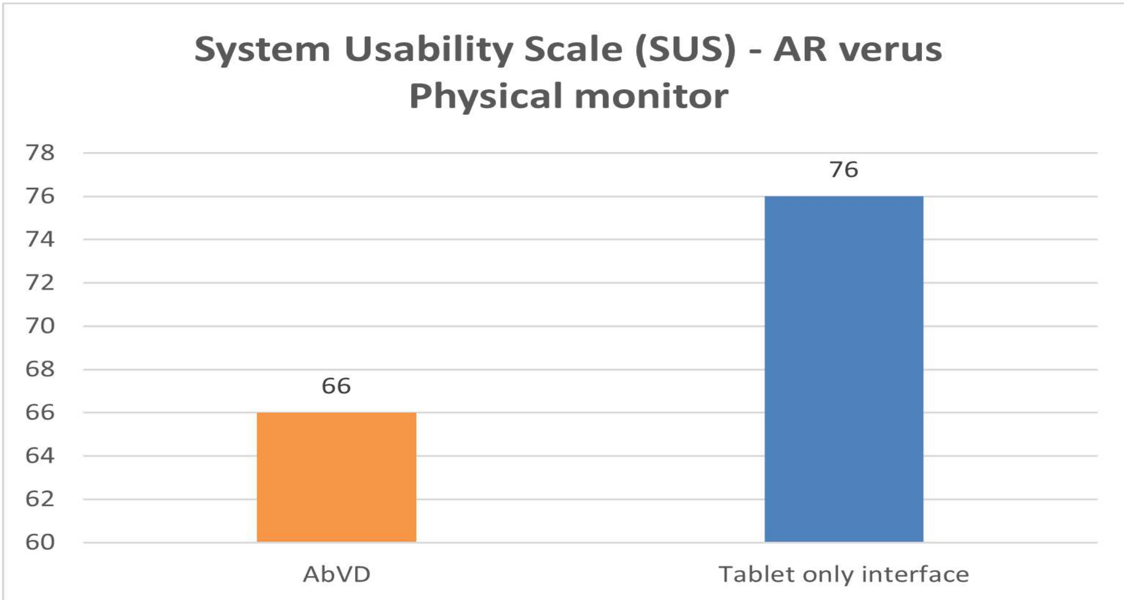


Figure 5.13: System usability scores comparison

each participants and made a note of them. The summary of each tasks are illustrated below.

Finding data points in single layer - Toggle On and Off tasks

The set of tasks requires the participants to toggle on one AR layer at a time and perform the tasks. The participants in a seated position analyzed the data in two ways. In the first one, they came closer to the AR layers until they felt the ticks' numbers were visible. Then they used their finger to match a data point in X-Axis (Epoch) to the Y-Axis (Frequency/value) and read the values. The second way is that the participants came close to the AR layers, adjusting their head orientations as needed to see the layer, and found the data point values. The participants during the interview session referred to seated and toggle tasks as easy since the number of layers is less. They also felt that "Having control over the number of AR layers is helpful." The average time taken by participants in AbVD for the toggle tasks(in mm:ss) is 2:40 seconds, and the accuracy is better, with a score of 0.82. We identified the key strengths of toggling on and off from the interview data and the video logs. The participants can have substantial control over the AR layers, and they preferred to have fewer layers that they felt relevant to the task. The limitations of this approach with AR are clarity of the font size of the ticks and resolution of AR.

In AbVD the toggle the layers tasks 44 participants correctly toggled the feature asked by the researcher during the task. 4 participants expressed confusion when switching between F3 and F4 layers. In tablet 40 participants toggled the feature correctly and 4 expressed logical confusion on switching between alpha and beta in F3 and F4.

On the other hand, physical monitors had a slight advantage in terms of head orientation and resting position. The participants performed the tasks on tablets and answered the questions without adjusting their head orientation. The participants used their fingers and pointed over the data point over the specific epoch mentioned in the task list and hovered their fingers over the Y-axis to identify the frequency or value of valence and arousal. The participants also looked at the tablet and said the value without using their fingers to match it. The accuracy yielded by the toggle tasks are same as AR, which is 0.82, and the average time taken(in mm:ss) is 2:03. The participants had prior experience using the tablet computer, which left them with just the necessity to learn about the user interface and types of time series data.

Finding data points in a seated position from an angle - View from an angle tasks

The set of tasks requires the participants to lean back to view the augmented reality layers from an angle where they do not overlap. All the AR layers are toggled on during the whole task set. The participants used their fingers similar to the toggle task and matched the X and Y values to answer the question in the task list. Despite leaning back and viewing from an angle, the participants adjusted their head orientation a little closer to the AR layers since they had to make sure the frequency and epoch values were correct due to the limitations in resolution and font size of the tick values. The participants mentioned that working with four AR layers together was challenging in the interview. The X and Y axis values are hard to read when layers overlap.

The average accuracy of this set of tasks is 0.65, and the average time taken(in mm:ss) is 2:20. The accuracy was impacted by the number of layers and the overlapping layers. The strength of the viewing from an angling method is the ability to visually distinguish different layers in Augmented reality when compared to viewing all the graphs together on the tablet. The limitations are resolution, font size of the tick values, and some efforts put by the participants to adjust their head orientation to perform the tasks. On the tablet, the participants performed the tasks without adjusting their head orientation though viewing all the graphs together simultaneously on the tablet is challenging to read the data peaks since all the graphs overlapped each other. The accuracy of 0.63 is lower than the AR accuracy of 0.65, and the average time taken by participants in tablet only interface(in mm:ss) is 1:45. The participants' familiarity with the tablet helped them perform the tasks faster than the AR, though overlapping multiple line graphs resulted in lower accuracy.

When the researcher was describing the tasks the participants understood to toggle all the layers on in both tablet+AR and tablet interface. 30 participants leaned close to tablet+AR since the tick values are small when viewed from an angle. During interviews a significant number of participants mentioned that if the font size of the tick values are larger it could make the values easier to read from an angle. When the participants came closer to view the layers, the ticks and lines overlapped that caused some additional effort to read the values. One participant P10 with slight experience using AR stated in interview, "Its quite hard to see when the layers overlap with each other". Another participant P34 with slight experience using AR said, "Tasks should be accompanied with additional features such as grid or slider for reading the values easier.

Finding data points by looking through the AR layers in a standing position - Stand up and look down tasks

The task list requires the participant to stand up and look through the AR layers to answer the questions. Participants said, "It is difficult to see the bottom-most layer in AR during the interviews." Though the participant liked the visual distinction of layers, the accuracy of 0.68 is better than the tablet accuracy of 0.51. The participants spent more time(in mm:ss) of 2:06 seconds compared to tablet's 1:37 seconds. The participants said it was difficult to analyze the data with four layers toggled on during the interviews. In video analysis, we found that participants bent down to come closer to the AR layers to read the values, especially when performing tasks in the bottom layer close to the display. The participants said that it is challenging to read the values further down due to overlapping layers. The key benefit of this approach to analyzing the data is the ability to visually distinguish the layers and compare the values in the layers.

In video analysis and audio transcripts from think-aloud, we found that participants quickly distinguished the layers using the colors and the legend. The size of the line graphs in the bottom layers presenting valence and arousal are thick to enable better visual distinction and readability. The visual distinction also helped in better comparison between the layers. The main limitation of this approach is the number of layers and the font size of the tick values. The resolution of AR is also a limitation when analyzing multiple graphs simultaneously. Many participants expressed that having control over the number of layers and a grid to enable better readability of the graphs could help analyze the time series data better.

Out of 48 participants, 45 stood up and looked at the AR layers from the top and the participants distinguished the layers using colors. One participant said that "Valence, then I have to look at blue color line" and observed the values accordingly. 27 participants informed tablet+AR are visually distinguishable than in tablets. In the tablet-only interface participants performed the tasks by looking into all 4 graphs that are overlaid on top of each other. A participant P46 during the tablet-only tasks said "Its hard to see when multiple graphs overlap at the same point".

Use your own approach tasks

The participants can use their approach in the task list. The participants preferred toggling the layers off and keeping only the layers necessary to perform the tasks. Video analysis and interview data showed that the most preferred way to accomplish the tasks is seated and toggle on and off the AR layers approach. The participants preferred a seated position and worked the best with little physical effort in head orientation and resting position. The task accuracy in AR and physical monitors is similar, with a value of 0.68. The participants took average(in mm:ss) of 2:02 seconds in AR and 1:36 seconds in the tablet. The strengths of this approach are adequate to control given to the participants. The familiarity with the interface at this point proved to be helpful for the participant in choosing which approach suits them best for them. The visual distinction of layers and legends and familiarity with the tablet's user interface made the participants perform tasks without any guidance on the head orientation or the resting position. During the interview, the participant said that controlling the number of layers and spacing between the layers would benefit data analysis.

A learning effect was observed in terms of participant using their preferred way to perform the tasks. In above display we can perform the tasks by toggling the layers on or off, keeping all the layers on and viewing the layers from any angle when seated or standing. 20 participants used multiple layers only for comparison tasks such as finding the greater value of alpha or beta in F3 and F4 layers. 3 participants kept all 4 layers on during the tasks. During interviews participants expressed if they have more control over the number of layers displayed and spacing between the layers then it would make the tasks easier. In tablet-only interface 12 participants used multiple layers only for comparison tasks and 30 participants used the toggle feature to keep only one layer on at a time and performed the tasks.

5.3.2 Think-aloud

We used retrospective probing during the interview to ask follow up questions based on participants' experience.

Impact of layering in BCI data comprehension

We probed the participants on how the layering(HA) helped in terms of data comprehension in your perspective. Participants felt layering helps to get different perspectives of BCI data. 7 participants said layering helps to get different perspectives of data by looking at the layers. One way is to look at the layers in different angles and the other is visually distinguishing each data presented in layer which reduces complexity.

10 participants said that the layering has positive impact in terms of data comprehension. Participant P3 mentioned that layering has a positive impact depending on the task since it reduced the number of times we interact with the tablet and click on toggle button and bring up the data. The number of layers do not matter if we have means to easily read the data. Participant P1 with experience using AR devices quoted during interview, “Number of layers do not matter if movable axis or grid is present to tell what X and Y is”. The participants also felt that if the data is complex having different layers can help keep track of the different data. Participant P37 quoted by saying ”It is useful have a third dimension like AR for visualizing complex data in different layers and keep track of them”.

5.4 Qualitative data analysis AbVD - interviews

5.4.1 Visual distinction of data in AR

The participants felt that the peaks and lows of time series data are clear and easily identifiable AbVD. During interviews 10 participants said that the layers are more distinguishable in AR than in the tablets in above display.

5.4.2 Advantages of AR layers

During the interviews when we asked the participants on advantages of layering(HA), The participants felt that visual distinction of four layers in BCI helped them identify individual features and perform data analysis tasks. 17 participants said that distributing the data in different layers helped them compare the values, and observing the layers from different angles helped them get different data perspectives. Layering also helped participants quickly identify values in individual layers, which is problematic on a tablet due to overlapping two or more graphs at the same point.

5.4.3 Toggle feature and number of layers

Participants expressed that four layers are a bit challenging to match X and Y values, especially when they adjust their head orientation which can cause the graphs to overlap. 30 participants mentioned that working with 4 layers is difficult and two layers can be used instead. 30 participants said they prefer to have control over the number of layers displayed in accordance to the task. 5 participants felt that the number of layers might not matter if values could be determined without requiring alignment with the ticks on the X and Y-axis.

5.5 Summary of Data Analysis - AbVD

We present the summarize the findings from data analysis in Table 5.4.

AbVD - Summary of data analysis	
Measure	Outcome
Accuracy	The AbVR interface yielded more accuracy than tablet only interface in tasks where participants identified data points in each layer i.e., F3, F4, valence and arousal in a standing position.
Time taken	Participants took significant more time in all four task groups of AbVD than tablet only interface due to more time required to adjust their head and read the X and Y values in AR.
System usability	SUS scores of the tablet only interface are significantly higher than those of AbVR. Participants felt the number of layers made it complex to read X and Y values.
TLX	TLX scores of AbVD is significantly higher than tablet only interface.
Custom questionnaire	Participants significantly rated tablet only interface higher than AbVD for finding X and Y values and viewing multiple graphs together

Table 5.4: AbVD - Summary of data analysis

5.6 Statistical data analysis results for Around display (ArVD)

In this section we present statistical test results for primary measures of ArVD: Task accuracy, time taken for tasks in Group 1 and Group 2. To reject H0B both accuracy and time taken must return significant results. We present normal distribution results and statistical results for task accuracy, time taken, system usability scores and task load scores. Similar to AbVD, we present behavioral analysis results from video observations and think aloud data. Qualitative analysis results of semi-structured interview and a summary of data analysis on ArVD is presented in later portions of this section.

5.6.1 Accuracy - Testing hypothesis HB1

We performed statistical tests on Group 1 where participants used focus+context feature and Group 2 where participants used their own approach to complete the tasks. Task accuracy and time taken for Group 1 and Group 2 tasks are presented in Table 5.5. The visual summary of task accuracy for both groups are as seen in Figure 5.14 and 5.15.

Around display			
Platform	Task type	Average time taken (MM:SS)	Accuracy
Tablet + AR	Training tasks	05:02	-
	Use focus points and look both sides	06:05	0.86
	Use your own approach	04:48	0.82
Tablet only	Training tasks	05:02	-
	Focus point and swipe	06:05	0.81
	Use your own approach	05:05	0.80

Table 5.5: Average time taken for each tasks in around display

Identifying data points using Focus+context tasks

The Group 1 tasks required the participants to adjust the view of time series data based on the specific focus point i.e., Epoch clicked in the tablet. The participant then looked on both sides of the tablet to find the valence and arousal value from a specific range. We calculated task accuracy for Group 1 and performed test for normality using Shapiro-Wilk test. The results ($W = 0.96, p = 0.01$) did not indicate normal distribution The Kruskal-Wallis test indicated a significant difference between ArVD and tablet only interface in task accuracy ($\chi^2 = 11.82, p < .001, df = 1,$) with moderate effect size (ϵ^2=0.12). Task accuracy in ArVD ($M = 0.86, SD = 0.05$) is significantly higher than the tablet ($M = 0.81, SD = 0.06$). After Bonferroni correction, $\alpha_{new} = 0.01$

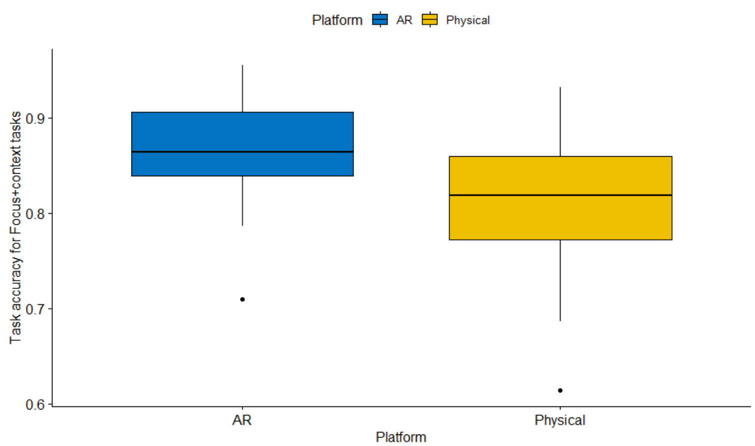


Figure 5.14: Accuracy of focus+context tasks

Find data points using own approach - Use your own approach tasks

We calculated accuracy for Group 2 tasks where the participants are asked to use their own approach to find valence and arousal values in longer duration time-series graph. The Shapiro-Wilk test did indicate a normal distribution ($W = 0.97, p = 0.04$). The Kruskal-Wallis test did not indicate any significant difference between ArVD and tablet only interface in terms of accuracy($\chi^2 = 0.18, p = 0.67, df = 1$) with negligible effect size (ϵ^2=0.002). The mean and standard deviation of AR and tablet are as follows, ArVD ($M = 0.81, SD = 0.1$) and tablet ($M = 0.80, SD = 0.1$). After Bonferroni correction, $\alpha_{new} = 1$

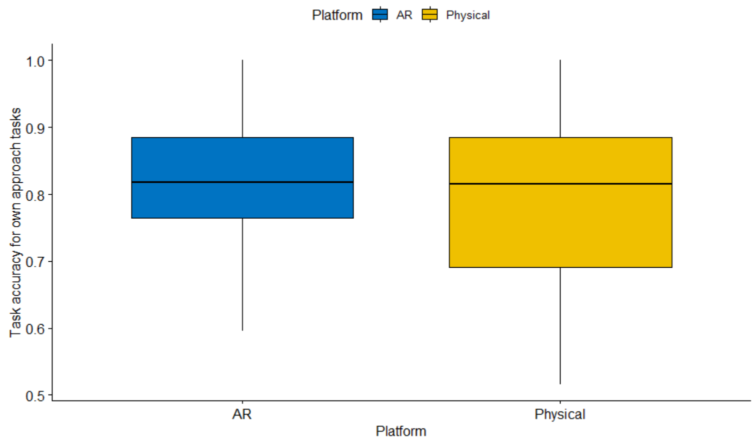


Figure 5.15: Accuracy your use own approach tasks

5.6.2 Time taken- Testing hypothesis HB2

We performed statistical tests on time taken for both group 1 and 2 from ArVD experiment. The following subsections will present the results from statistical analysis. The visual summary of task accuracy for both groups are as seen in Figure 5.16 and 5.17.

Focus points and look around tasks

We calculated time taken for focus+context tasks(Group 1) and the Shapiro-Wilk test for normality indicated that data is not normally distributed ($W = 0.93, p < .001$). The Kruskal-Wallis test indicated no significant difference in time taken between ArVD and tablet only interface for Group 1 tasks ($\chi^2 = 0.32, p = 0.57, df = 1$) with negligible effect size(ϵ^2=0.003). The mean and standard deviation of the time taken in AR and tablet are as follows, ArVD ($M = 5.90, SD = 1.51$) and tablet ($M = 5.91, SD = 2.16$). After Bonferroni's correction, $\alpha_{new} = 1$.

Use your own approach tasks

We calculated the time taken for the task set that requests participants to use their own approach to find valence and arousal values. The Shapiro-Wilk test for normality indicated that the data is different from normal distribution ($W = 0.96603, p = 0.01365$). The Kruskal-Wallis did not indicate any significant difference in time taken between ArVD ($\chi^2 = 0.08, p = 0.78, df = 1$) with negligible effect size (ϵ^2=0.001).

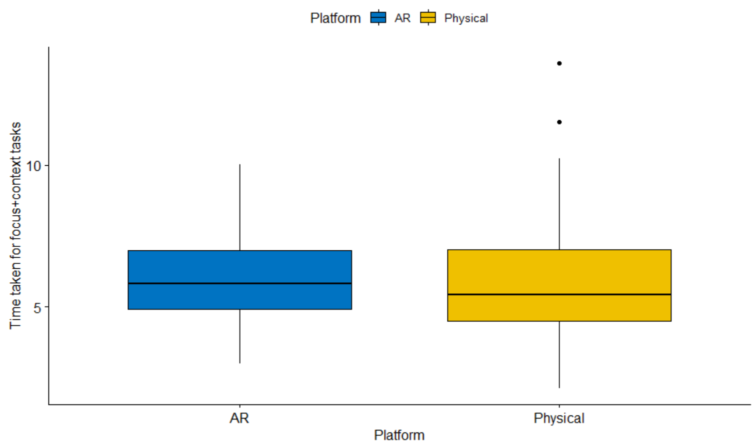


Figure 5.16: Time taken for focus+context tasks

The mean and standard deviation for time taken for Group 2 tasks are as follows, ArVD ($M = 4.65, SD = 1.19$) and tablet ($M = 4.92, SD = 1.76$). After Bonferroni correction, $\alpha_{new} = 1$.

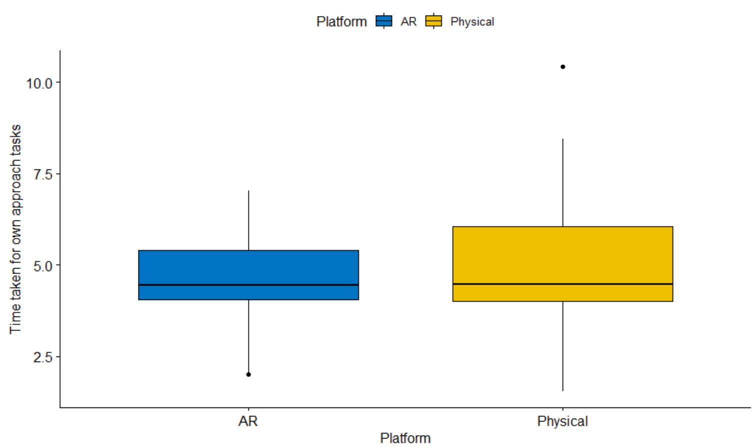
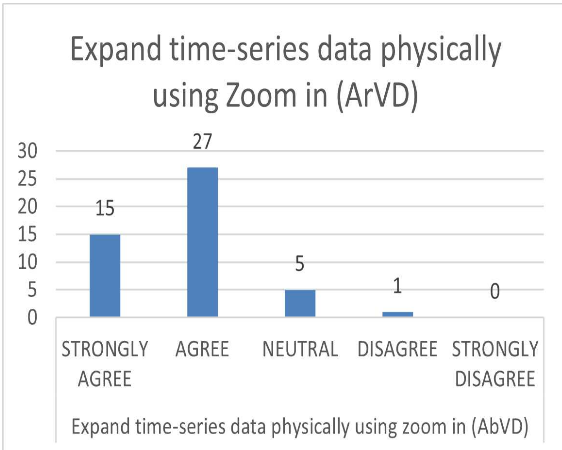


Figure 5.17: Time taken for use your approach tasks

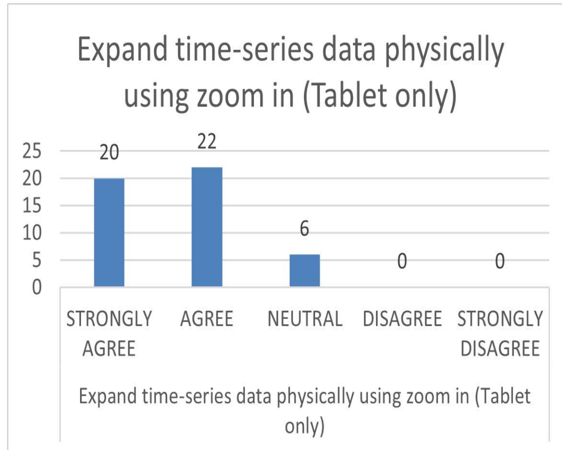
5.6.3 Custom questionnaire analysis ArVD

We used statistical tests similar to AbVD custom questionnaire analysis for ArVD. The responses for questionnaire are presented in Figure 5.18 and Figure 5.19. The statistical results are presented in Table 5.6

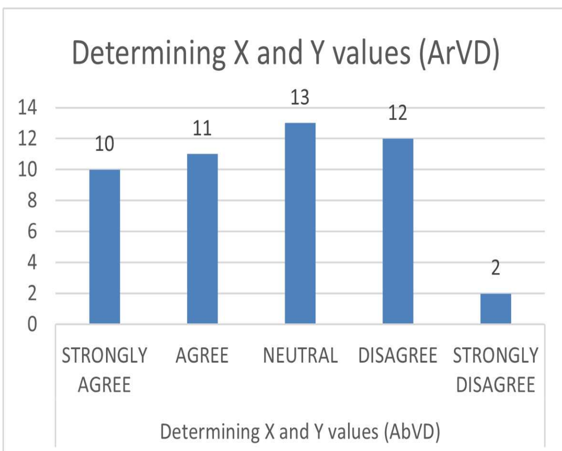
Figure 5.18: ArVD custom questionnaire



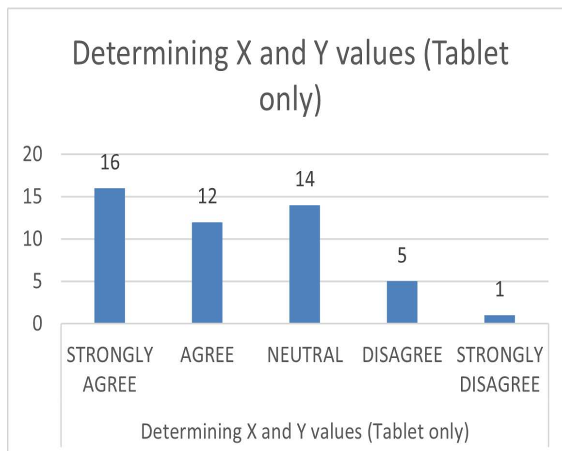
(a) g



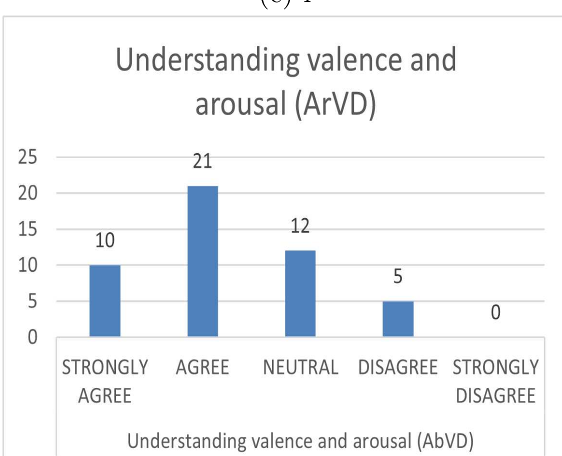
(b) h



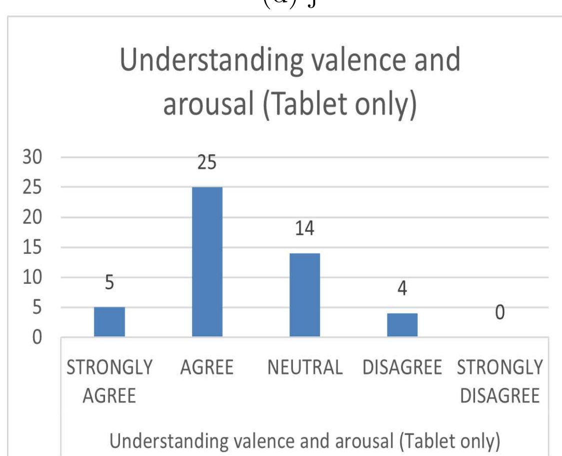
(c) i



(d) j



(e) k



(f) l

Figure 5.19: ArVD custom questionnaire (Continued)

5.6.4 NASA TLX

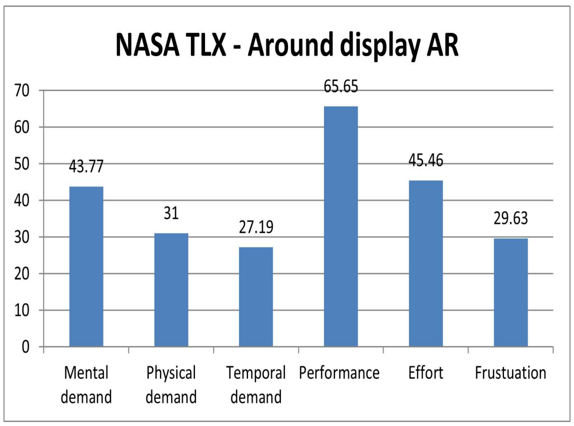
In the ArVD experiment, the difference between AR's task load(TLX) and physical monitors is not significantly high. In terms of indiviual aspects of ArVD, participants ratings pointed out physical demand significantly higher in ArVD than the tablet only interface. In around display AR, we had only one AR layer; hence it was easy for the participants to keep track of changes and identify the values. The unweighted TLX score for AR is 40.45 and for the physical monitors is 39.18.

Mann-Whitney U test did not indicate a significant difference between overall TLX scores of ArVD and tablet only interface ($W = 1323.5, p = 0.2099$) with small effect size($r = 0.12$). Through video analysis it is observed that participants had difficulty reading the values of data points that are located far away and they have to adjust their position to see the data point and read its value. Statistical analysis on individual factors of task load e.g. Mental demand, physical demand etc., indicated that there is no significant difference in the scores of individual factors between AbVD and tablet only interface. Statistical results of NASA TLX are as seen in Table 5.7. The data summary for each task load factor is as seen in Figure 5.21.

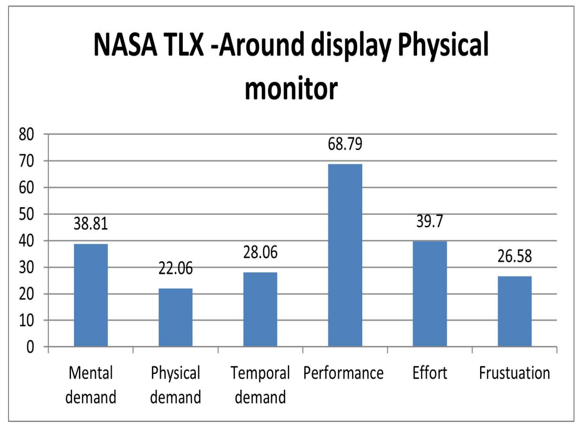
5.6.5 System usability score

The system usability score of the Augmented reality is 69 which points to marginal rating of 'C' and the physical monitors is 73 which points to acceptable rating of 'B-'. During video analysis we observed that in physical monitors the participants used more swipes to navigate through the data and shift left and shift right feature is not used extensively.

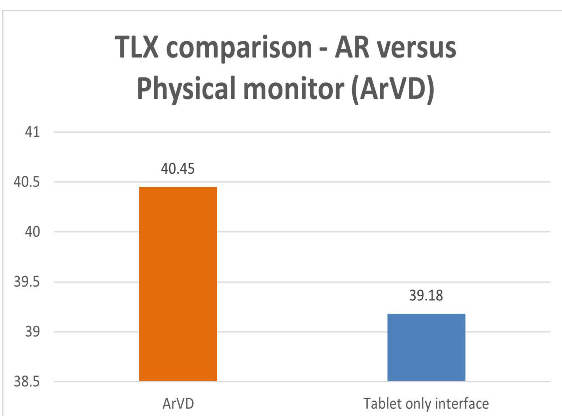
The self-reported system usability score for the ArVD interface and the tablet-only interface are tested significant difference using Mann-Whitney U test, ($W = 1038, p = 0.40$) with negligible effect size ($r = -0.08$). The results did not indicate any significant difference between system usability scores of ArVD ($Mdn = 73$) and tablet only interface ($Mdn = 73$). SUS scores of ArVD and tablet only interface are as seen in Figure 5.22.



(a) ArVD

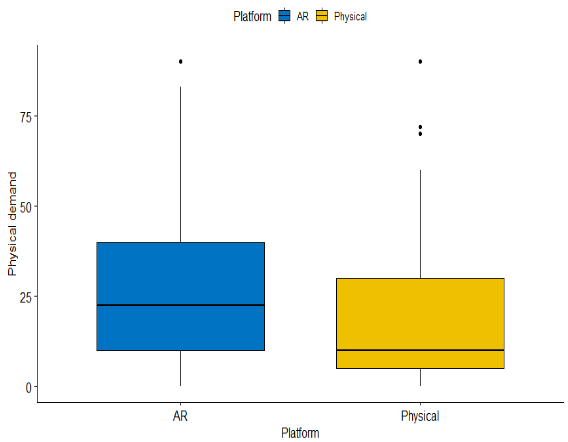


(b) Tablet only interface

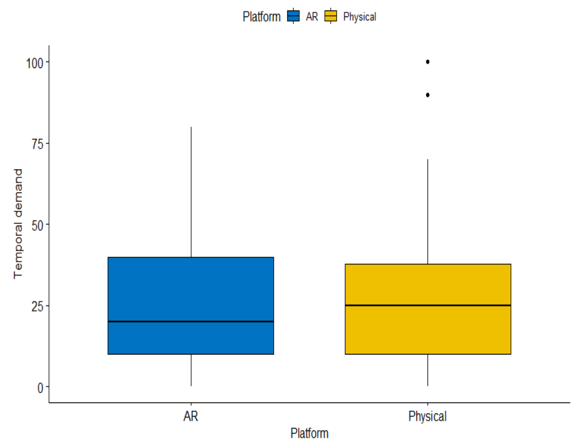


(c) Task load comparison

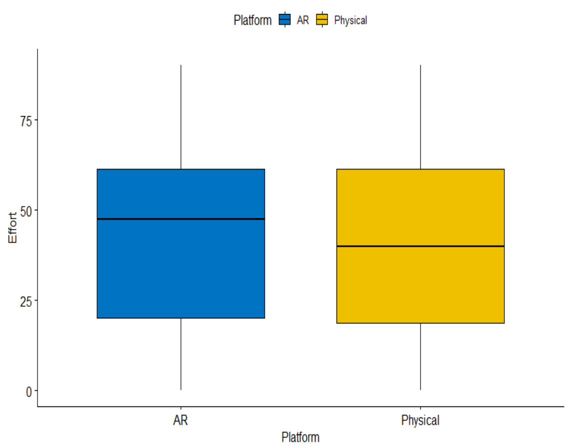
Figure 5.20: ArVD NASA-TLX



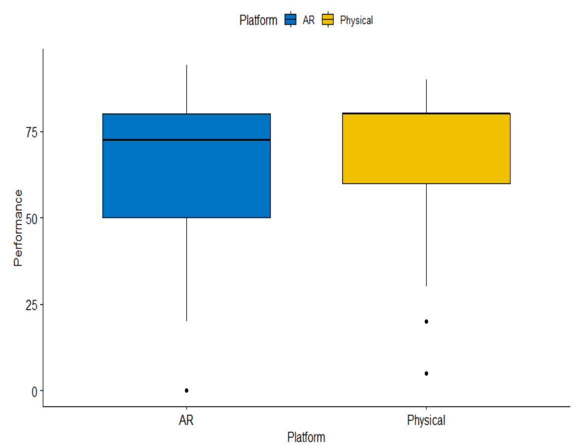
(a) Physical demand



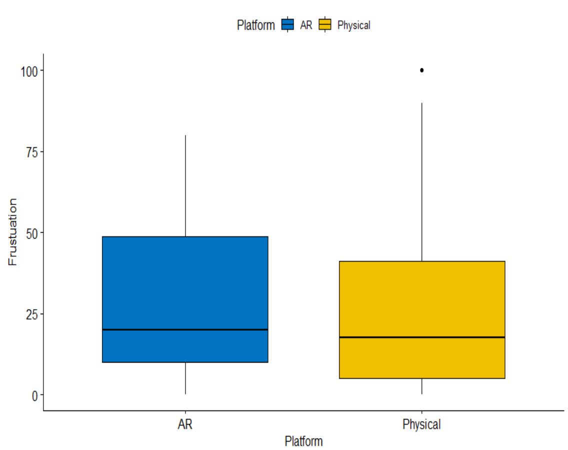
(b) Temporal demand



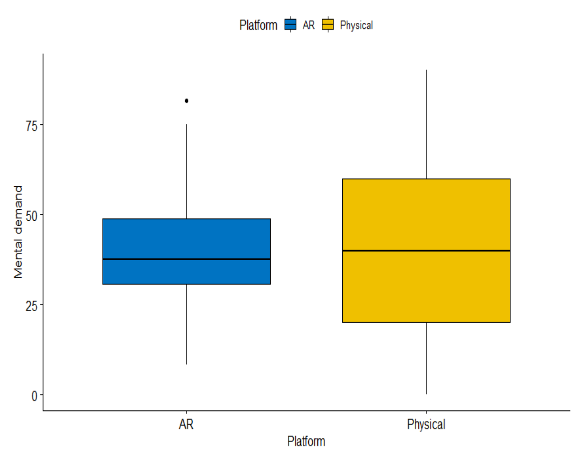
(c) Effort



(d) Performance



(e) Frustration



(f) Mental demand

Figure 5.21: ArVD - Comparison of TLX factors

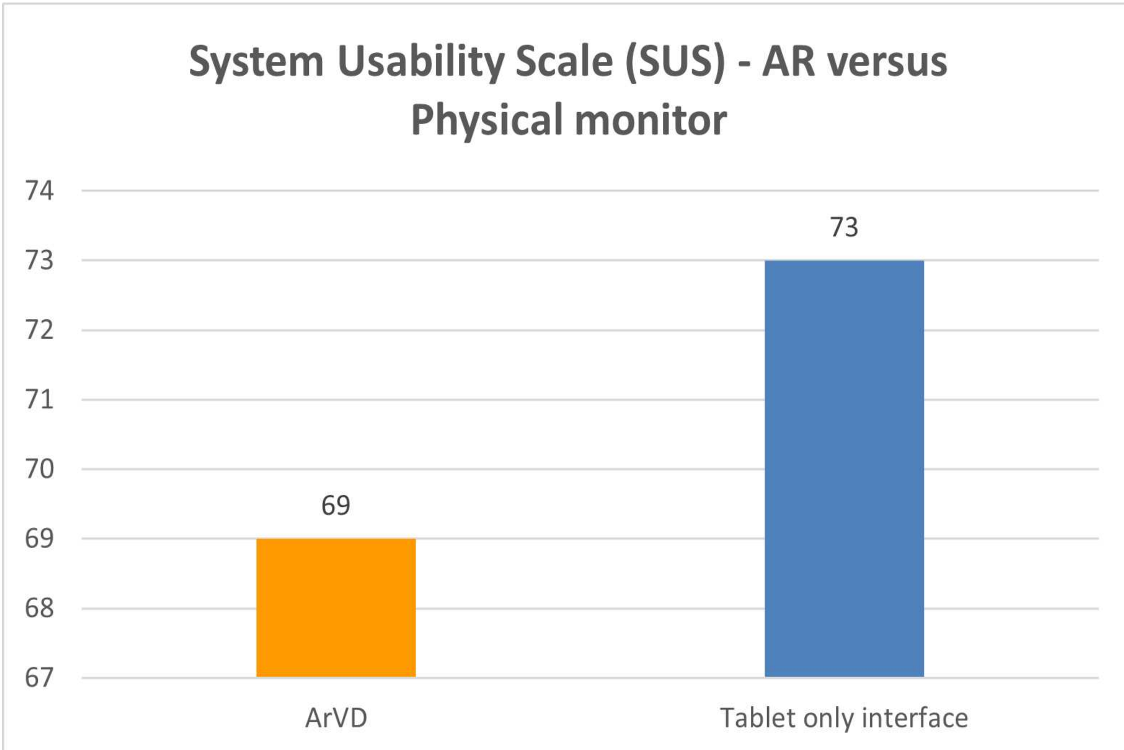


Figure 5.22: System usability score comparison

5.7 Behaviour analysis for ArVD

5.7.1 Video observations

Finding data points using focus+context view - Focus points and look around tasks

We made observations from the video logs on specific actions, such as how the participant performed the focus points tasks. The participants looked at both sides of the augmented reality, moved their fingers to match the X and Y axis values, and answered the questions. In the find values between longer range tasks, When the X and Y axis values are far, the participants adjusted their head orientation, moved closer to the data point, and answered the question. The resolution in augmented reality is less when compared to tablets. Hence participants put some effort into reading the values. The font size is not large enough for them when the data point is far. Hence they moved their head closer to the data point to ensure the values. During the interviews, most participants liked the data representation around the display.

The task accuracy of the participants in augmented reality is greater than the physical monitors for the focus points tasks. The participants extensively used swipe for tablets, and in AR, they looked at both sides of the extended display and answered the questions. The average time taken in ArVD(in mm:ss) is 6:05 and tablet only interface is 6:05.

In the focus+context tasks, 42 participants clicked on the focus point instructed by the researcher and looked at the extended time series data in AR from both sides of the tablet and identified the data points. The 42 participants did not use shift-left/shift-right feature to adjust the view of data. 5 participants moved around both sides of the AR in seated position to find the data points. 10 participants stood up and walked closer to the data points in AR and read the values. One participant P12 during the interview stated "The values are hard to read if its far away". Another participant P1 stated "The graph in AR sometimes go through the wall if shifted to extreme left and the data points are far away". In the tablet-only interface the participants swiped using the finger, matched the value to the Y-axis and identified the value. One participant P5 stated "It is difficult to swipe for long time to reach the data point". In tablet-only interface 40 participants used swipe to navigate through the data and identify the data points. 2 participants used fingers in both hands to swipe the data on both sides.

In terms of logical confusion when performing the tasks that requires the participant to click on a focus point and identify data points within a certain epoch intervals, 25 participants asked the researcher "What is meant by epoch intervals?" and the researcher clarified it during the training tasks before moving to the main task sets. When performing the task that requires the participant to look both sides of AR to identify the extend of time-series data, 20 participants asked "What do you mean by extent of time-series data?" and the researcher clarified it to the participants.

Use your own approach tasks

In use your own approach tasks, 31 participants clicked on the focus point and looked both sides of the AR to identify the data point, 42 participants did not use the shift-left and shift right feature. 10 participants stood up and walked closer to the AR and identified the data points. 5 participants moved closer to the data point in AR in a seated position and identified the data points. Only 3 participants used the combination of focus-points and shift features to identify data points. In tablet-only interface 40 participants used swipe to navigate to the data point and identify the value. We also observed 5 participants used the zoom-out feature to identify the highest peak in the time series data.

The participants preferred clicking on the focus-point and looking both sides of the AR and finding the data point in use your own approach tasks. One participant P40 who had occasional experience with AR stated, "It is beneficial to see the whole time series data and navigate through it synchronously with tablet and AR." A key observation is that the participants decide when to use the extended display (Zoom in) and when to use just the tablet by zoom-out in use your approach tasks. During the interview, participants said that a grid or a sliding Y-axis could be helpful to read the values better. The average time taken by participants for tasks(in mm:ss) in ArVD is 4:48 and tablet only interface is 5:05

5.7.2 Think-aloud

Similar to AbVD, we used retrospective probing during interview and we received inputs from the participants regarding their experience with ArVD.

ArVD reduced interaction with tablet

When we asked the participants on how focus+context(HB) helped in terms of data comprehension, participant felt ArVD reduced the number of time we interact with the tablet to infer from the data. 10 participants said ArVD reduces interaction with tablet when working with large data. The participant P3 when probed regarding the ArVD interface mentioned he liked moved his head to look around and read from data than interacting with the tablet. The participant P48 during the interview said, in case if someone does not want to spend time reading or interacting, presenting the whole data helped them to comprehend the data better.

5.8 Qualitative data analysis - ArVD interviews

5.8.1 Impact of focus+context view in terms of data comprehension in BCI

When we asked the participants on how focus+context(HB) helped in terms of data comprehension, participants felt ArVD can support visualizing large data without screen size limitation. 34 participants said that ArVD helps to view large time-series data. Participant P27 who is familiar with AR stated, “ArVD made use of the infinite screen space to present the BCI data and many devices have small screens to visualize such data”. Another participant P3 stated “I see the peaks in valence and arousal data clearly in around display”. On the other hand, the tablet display has display limitations due to screen size. Hence participants expressed that AR is very beneficial for viewing extensive time-series data that can extend from both sides of the tablet. In terms of data analysis, 12 participants expressed that AR is beneficial since AR helped them analyze data by just turning their head left or right to find the values.

5.8.2 ArVD required limited interaction

In semi-structured interviews, 8 participants said ArVD reduces the need to scroll the data multiple times to reach from one point to another. In tablet-only interface, participants had to swipe the screen multiple times to navigate through the time series data. 4 participants also expressed that Tablet + HMD AR interface is very interactive in navigating from one end of time-series data to another and switching between valence and arousal time series data.

5.9 Summary of Data Analysis - ArVD

We present the summary of data analysis of ArVD in Table 5.8.

Statistical analysis on custom questionnaire - ArVD						
Question	W	p	α_{new}	AbVD (Mdn)	Tablet (Mdn)	ϵ^2
Viewing large time series data clearly	1051	0.40	1	4	4	0.01
Panning longer duration time-series data	928	0.05	0.3	5	5	0.04
Expand the time-series data physically using Zoom in	1044	0.38	1	4	4	0.01
Shrink the time-series data physically using zoom out	1049	0.40	1	4	4	0.01
Determining X and Y values	898	0.06	0.36	3	4	0.04
Understanding valence and arousal	1237	0.50	1	4	4	0.004

Table 5.6: ArVD - Statistical analysis results on custom questionnaire responses

Statistical analysis on perceived task load						
Task load	W	p	ArVD (Mdn)	Tablet (Md)	Effect size (r)	α_{new}
Mental demand	1270	0.07	37.5	40	0.08	0.42
Physical demand	1440.5	0.03	22.5	10	0.21	0.20
Temporal demand	1142	0.94	20	25	<.001	1
Performance	1071.5	0.54	72.5	80	<.001	1
Effort	1245	0.50	47.5	40	0.07	1
Frustration	1240	0.51	20	17.5	0.07	1

Table 5.7: NASA TLX - Perceived task load summary for ArVD

ArVD - Summary of data analysis	
Measure	Outcome
Accuracy	ArVD yielded more accuracy than tablet only interface in tasks that involved finding data points in longer duration time-series data in focus+context view.
Time taken	In ArVD there is no significant difference in time taken for the tasks in ArVD and tablet-only interface.
System usability	Through SUS scale the scores, there is no significant difference in scores of ArVD and tablet-only interface.
TLX	There is no significant difference between self reported TLX scores of ArVD and tablet only interface
Custom questionnaire	There is no significant difference between ratings of ArVD and tablet only interface.

Table 5.8: ArVD - Summary of data analysis

5.10 Thematic analysis results from semi-structured interviews

Based on the semi-structured interviews with the participants. We performed thematic analysis and divided the participants' feedback into themes as follows.

5.10.1 User experience

Tablet bias

The participants are generally comfortable using the tablet computer due to their previous experience using the tablets. During interview, 12 participant informed about the tablet bias. One participant from architecture program stated "Maybe I prefer using tablet because I am familiar using it". The experience of using AR plays a significant role in performance, and some significant experience using the interface will help the participants perform tasks better for first-time users. The new participants in AR felt that the experiment is very engaging. The participants felt that AR has excellent potential to demonstrate complex terminologies and relationships in science better. Having both tablet and tablet with augmented reality visualization could help the researcher gain different data perspectives.

Advantages of AR layers

The participants expressed layering gave them new perspectives of data and seeing the graphs separately in layers made each graphs visually distinguishable. Participants also expressed viewing angle is important when viewing multiple graphs in layers to perceive the salient data points in the plot.

First time AR users

Four first time AR users among the participants said; experience using the interface, acumen and technical know-how plays a role in both completing tasks and adapting to using hybrid interface.

Task difficulty

The participants felt that the tasks were more similar and were easy to understand and keep track of the flow. Most of the tasks in the BCI above the display are comparing different layers and identifying values. 4 participants in interview said that tasks are repetitive (finding data points). For the around the display is to find specific points within different ranges. The participants expressed that the above and around display interface design is good, and it helped them identify the tasks better.

Advantages of viewing large time-series in AbVD

In semi-structured interview, we asked participants about the perceived advantages of viewing longer duration time-series in ArVD, participants said it was beneficial to see the entire time-series graphs and identifying salient data points by simply turning their head left or right.

Physical constraints

The participant felt that the HMD weighed more at time for specific tasks such as stand up and look down and adjusting the head orientation. Wearing the headset for a longer time also caused ergonomic issues. 12 participants mentioned in interviews that HMD feels heavy on their neck. Some participants expressed that they experienced neck pain when they wore headsets for a longer period of time. Due to the physical constraints the participants felt that if they have to use an interface in order to perform data analysis tasks for a longer duration, they felt tablets are better.

5.10.2 Implementation

Resolution

The resolution of the visual elements presented in augmented reality is low compared to the content presented on the tablet. The participants felt that numbers are hard to read if they are far. The resolution of the time-series graph in AR could be better, and the font size could be larger for the axis ticks. However, the colors blended well for the above display, which has tasks for seeing through the time-series graphs from the above. The resolution for the HoloLens is a known limitation.

Grid to identifying X and Y values

The participants felt that in order to read the graphs better, a grid can be introduced in above display AR and around display AR. During interviews 16 participants reported that if there is a grid or slider added to the time-series graphs then it would be easier to find the data points. In ArVD AR, a movable Y-axis that can be controlled by the tablet will be beneficial to read the peaks better if the data point is far. The tick marks in the X and Y axis looked smaller when a participant is in a seated position and looked at a data point that is far away on other's end.

Challenges with number of AR layers

When asked about the experience using AR layers, participants expressed that working with 4 layers is challenging when layers overlap with each other. They also said that working with minimum number of layer i.e., 2 layers was easier. The participants expressed that in addition to having control over the number of layers using the toggle feature, provided that they have an option to adjust the space between the AR layers, it could help perform the tasks better with multiple layers. During interview we asked the participant if they wish to have control over the spacing between layers and number of layers. 30 participants reported that having control over the spacing between layers is beneficial according to the task. One participant P35 who is familiar using AR stated "It is beneficial to have spacing if I want to adjust the layers according to my height". They also felt that in specific tasks such as standing up and looking down, and viewing from an angle if they have an option to control the spacing between the layers could be very beneficial. Current spacing we used is 0.85 in Unity.

Calibration issues

We used a QR code to anchor the visualization to the tablet. 3 participants mentioned about calibration issues when the tablet is moved when the continuous QR tracking is disabled. For the most part, the alignment of AR layers is good. However, few participants felt that in BCI times, the calibration is not perfect and the AR layer's position is slightly off at times, and the tablet has to be manually adjusted a little bit.

5.10.3 Future applications

Live BCI data

We had 5 participants from neuroscience school in our study. When asked about the potential applications of AbVD and ArVD, the participants expressed live data visualization as time-series from a BCI device in the interfaces will be one potential future application.

General applications

We asked the participants to know what are the potential applications of AbVD and ArVD according to their thoughts. Participants expressed that time-series is generic and can be applied in different areas e.g., in a mathematical course in school, studying variations in time-series, bone morphology :- visualizing different layers in tissue using AR layers.

5.11 Review of findings in relation to the research questions

We recorded and analysed accuracy, system usability, TLX and time taken to complete the tasks for above display and around display. We tested our hypothesis for individual tasks, time taken for individual tasks and individual components of TLX. In terms of TLX and System usability we did not find significant impact that shows AR is better than tablets though they revealed important observations on what aspect could possibly make AR better in future. In terms of TLX the participants put more efforts into AR especially in above display due to the number of layers and challenges in reading X and Y values due to font size, resolution in AR and overlapping layers. In around display the participants are comfortable with single layer of AR though reading the values became a challenge if the values are situated further from the participant for example,if the tablet is centred at 1500 epochs, values at 5500 epochs are challenging to read.

5.11.1 Above display

Research question 1(RQ1)

From the AbVD experiment we are able to find answers to RQ1. Results from hypotheses testing are presented below

Hypothesis

To reject hypothesis H0A1 we took time taken as indicator and for hypothesis H0B2 we took task accuracy as indicator. Statistical results on task accuracy indicated that participants performed significantly more accurately in AbVD when compared to tablet-only interface for the tasks where participants stood up and looked through the AR layers. In terms of time taken our statistical results indicated that participants took more time in AbVD when compared to tablet-only interface. Hence **Hence only H0B2 can be rejected**.

User experience:

Perceived task load scores and system usability scores gave us insights about user experience with AbVD. Statistical results on perceived system usability indicated that participants preferred tablets to AbVD. Scores of individual factors in the task load indicated that physical demand and effort is significantly higher in AbVD when compared to tablet only interface. Performance scores in task load indicated that participants are more confident using tablets-only interface when compared to AbVD.

Answer to RQ1:

We did not find any significant difference in time taken with respect to HA1 though we managed to find significant difference in terms of task accuracy for HA2 favouring AbVD. To summarise the overall AbVD experiment to answer RQ1, Layering in AbVD helped participants locate salient data points significantly more accurately than tablet-only interface for tasks where participants stood up and looked through 4 AR layers to perceive data points. 40 participants did not use the toggle feature in the stand up and look down task set. As a part of interface feedback, participants rated tablet only interface significantly higher than AbVD for system usability. In terms of task load ratings, participants rated AbVD higher in terms of task load. Based on qualitative data from interviews, participants appreciated the AbVD for presenting different data layers more clearly than in physical monitors where the graphs tend to overlap. 17 participants expressed that layering the BCI data has its advantages in terms of comparing values between two graphs. 10 participants also expressed layers helped to distinguish the features clearly when compared to tablet only interface. One participant P17 with slight familiarity in AR stated, "Layering helped me to distinguish each graph clearly in augmented reality." Though 30 participants expressed working with 4 layers is challenging in terms of matching X and Y values of salient data points in the axes, 15 participants said that presence of the grid in each layer could be beneficial in future to match X and Y values of salient data points. As a part of future improvements, 15 participants said if there is a feature to reduce spacing between the layers in future it will be helpful for them to adjust the spacing according to their height. Having considered all the findings from the AbVD experiment, to answer RQ1 in a nutshell, presenting time-series plots in layers can help locate salient data points with limited interaction and identify relations accurately than tablet only interface in a specific viewing angle suitable to perceive data points without any obstruction such as layers overlapping to read X and Y axes values.

5.11.2 Around display

Research question 2(RQ2)

From the ArVD experiment we are able to find answers to RQ2. Results from hypotheses testing are presented below

Hypotheses

To reject hypothesis H0B1 we used time taken as primary indicator and to reject H0B2 we used accuracy as primary indicator. Our statistical results did not indicate any significant difference in time taken between ArVD and tablet only interface. However we found that participants' performed significantly more accurately in focus+context tasks when compared to tablet only interface.**Hence only H0B2 can be rejected**

User experience: Statistical analysis on perceived system usability scores did not indicate a significant difference between ArVD and tablet only interface. Overall NASA-TLX scores and scores of individual factors i.e.,Mental demand, physical demand, temporal demand performance, effort and frustration did not indicate significant difference between ArVD and tablet only interface.

Answer to RQ2:-

We did not find any difference in time taken with respect to HB1 though we find a significant difference in terms of accuracy for HB2 favoring ArVD. To summarise the overall ArVD experiment as an answer to RQ2, The ArVD interface using ArVD helped to locate salient data points significantly more accurately in a longer duration BCI time-series data in focus+context view. 41 participants did not use the shift-left or shift-right feature presented to them in the focus+context tasks. In the tasks where the participant could use their own approach, 42 participants did not use shift-left/shift-right to move the data for identifying the data points. One of the participants P37 from neuroscience program stated in interviews, “I felt good observing the entire time series in ArVD and observing the data move from left to right in sync with the focus portion of data in the tablet.”.

In the interview, participants expressed that AR is very beneficial to view the whole time series data all the time, which is otherwise not possible on tablets due to screen size limitations. The number of participants who reported tablet-only interface is better to find X and Y values is significantly higher than tablet+AR. The 15 participants expressed that a grid in AR or an adjustable slider could help read the X and Y values in AR better. In tablet+AR, 10 participants stood up and moved closer to the data point. For feedback about future improvements in the interview, a participant P42 from neuroscience program stated, “If there is a 360-degree visualization of the time-series data, then it would be easier to look around and find data points”. Having considered all the findings from the ArVD experiment, to answer RQ2 in a nutshell, extending the boundaries of the tablet screen using AR helped participants to locate salient data points in time-series data more accurately than zooming and panning in tablets when participants perceived the whole duration of time-series data in focus+context view with limited/almost no interaction with tablet for navigating the data.

Chapter 6

Discussion

In this chapter we discuss implications of the findings from our research and its relevance to previous work. We also summarized the contribution of our research, summary of limitations and future work in this chapter.

6.0.1 Lessons learnt from our research

Viewing angle is important to perceive values of the data points

The important contribution of our AbVD and ArVD research is the proof that AR can help to present specific challenging visualizations using tablet+AR. Tablet+AR performed better than tablets in terms of accuracy in AbVD for a specific viewing angle in standing position. On the other hand, the tablet could only present all four graphs together in the tablet, which overlap with each other. Hence presenting data in different layers when dealing with multivariate data is helpful for data comprehension in terms of accuracy. In the interview, participants from neuroscience background gave several examples of presenting the data in different layers. With adequate control in spacing between layers and the number of layers displayed simultaneously, the tablet+AR could present complex visualizations better. In ArVD, when we deal with extensive data such as a time series data from 0 to 7000 epoch, Tablet+AR could present the whole time series data better. The focus points feature to adjust the view of data and analyze the data by looking at the extended AR display from both sides of the tablet helped to perform the data analysis better than the tablet. When participants dealt with finding data points over a long range on the tablet, they swiped many times, and finding data points and remembering it was challenging. When the participant switched between time series data, the tablet display with the support of AR showed the entire graph. The participants also said it is visually engaging to see one time series graph changed to another, and observing the changes in peaks of entire time series data when switching between valence and arousal data is very helpful.

In earlier research, MARIVIS[1] and augmented reality for large interactive displays[48], the researchers demonstrated the use of augmented reality to present complex visualizations. Our contribution to research in presenting complex data through AR is the adoption of the display paradigms of extended displays and focus+context to present the brain computer interface data. Our approach is different in terms of the number of layers in the above display and the extended AR display's length around the display. The immersive analytics of BCI data using a novel hybrid tablet+AR interface is a new approach that did not exist in previous research in BCI.

Tasks performed in AR took more time than the ones in physical monitors

The participants mentioned in the interview that with adequate practice and experience in tablet+AR they could perform the tasks faster. Our results revealed that participants took more time in AR than in physical monitors. The accuracy is slightly more in augmented reality than in tablet though the participants took more time in augmented reality tasks. The main challenge is reading the values of the data points due to number of layers and smaller font size of the X and Y values. The participants look more time in looking at the data points, used their fingers to match the X and Y axes values. In tablets the participants can use the touch surface to navigate through the data and find the values that took less time. The future design should have more features to read the X and Y values of the data points such a grid. Our research contribution in comparing the accuracy and timestamp of the tablet+AR with the baseline tablet only condition is novel. The tablet is better in terms of time taken to complete the tasks, though there is a huge potential in tablet+AR interface in terms of innovative ways to analyse the data better. The accuracy and timestamps for each tasks are presented in Figure 6.1 and 6.2.

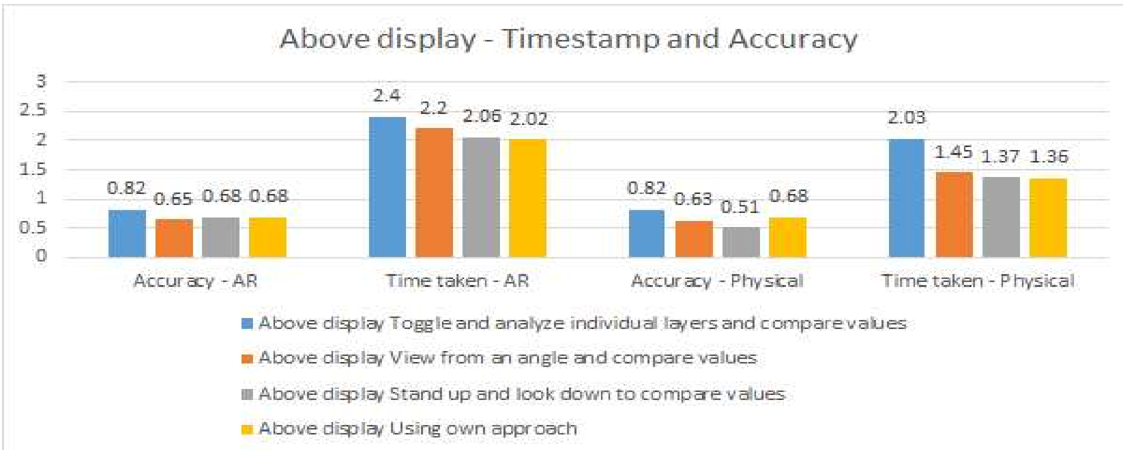


Figure 6.1: Above display - Time taken and Accuracy

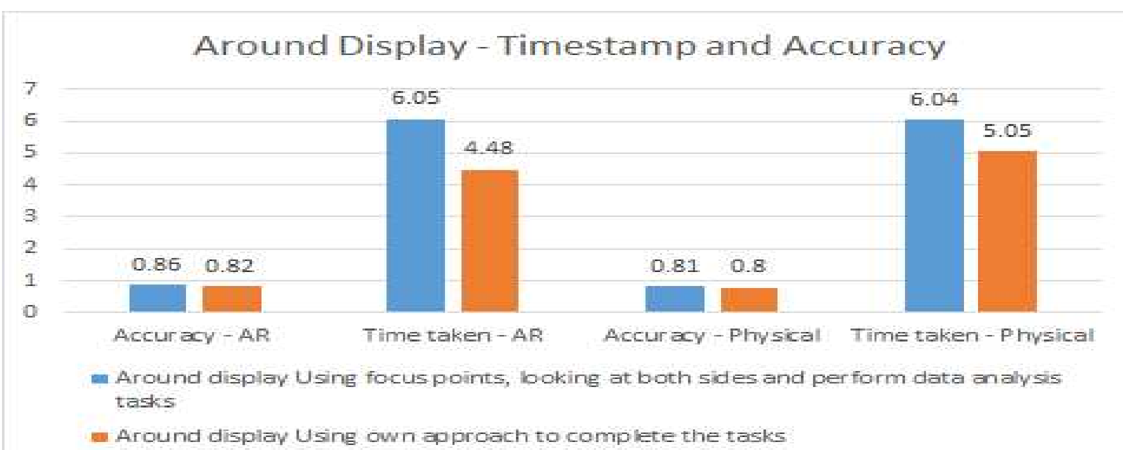


Figure 6.2: Around display - Time taken and Accuracy

Learning effect in AbVD and ArVD

The participants during the training tasks took more time to get familiar with the AR layers above the tablet. The training tasks in the ArVD took(in mm:ss) 3:10, and ArVD took 5:02 seconds. When the participants performed the toggle tasks, they learned about each AR layer and how to compare the layers and find which value is more than the other. The clear distinction of each layer helped them perform the stand-up, look down, and view from an angle tasks better. In ArVD, the use of focus points and look at both sides task yielded good accuracy, and the participants managed to analyze the time-series data by looking at both sides of the tablet. In using your own approach tasks, the participant took less time than the focus points tasks, which shows their increasing familiarity with the interface. The AbVD use your own approach tasks are completed within 2:00, and participants preferred to perform these tasks using the toggle, thereby turning off the layers whenever necessary. Their preference to control the number of AR layers displayed on top of the tablet is evident in the interviews when they expressed that working with four layers simultaneously demands increased mental effort. The resolution of AR poses some challenges in reading the numbers in graphs, and This can explain the time difference between AR tasks and physical monitor tasks. In ArVD use your own approach tasks, we observed 8 participants moved from their seated position and looked at the data point. During identifying the largest peak in the whole time series data tasks, we observed 10 participants zoomed out and answered the question instead of looking around and finding the peak. Other participants looked at both sides of the time series data in AR and answered the question. We observed participants asking questions about the AR layers and interface during the training tasks. Once the training tasks were completed, the participants got familiar with the interface and areas to look into when they performed the tasks.

Overall performance of AbVD and ArVD against tablet

AbVD and ArVD is significantly better than tablets in terms of accuracy though participants took more time in AR than in tablets. The participants performed better in terms of accuracy for focus points + look around tasks in around display and stand up and look through AR in around display. The participants preferred

AR to tablets in viewing large time series data and they liked navigating through the data using focus points. The participants also liked to observing changes in entire time series graphs when switching between valence and arousal in around display. In AbVD experiment participants preferred AR to tablets for visually distinguishing different layers of data and viewing multiple graphs together. The TLX data showed that task load in AR is high than in tablet, which explains why participants took more time for the AR tasks. The participants' familiarity with a tablet computer can be seen in the system usability scores, In which the SUS score of tablets is higher than AR. In interviews, the participant felt that though the Above and around display interface is engaging for first-time users, they can perform tasks better in the tablet + HMD AR interface with adequate training. The lesser resolution in AR also posed some difficulties in above and around display AR to read numbers on the X and Y axis far away. The resolution caused a significant amount of time taken in AR tasks. The participants, however, were able to perform tasks well just by looking at both sides of the tablet. Hence in the interface questionnaire and interviews, participants mentioned that looking at both sides and analyzing the time-series graph in ArVD interface is better than swiping multiple times on a tablet. In AbVD, the participants liked presenting the data in multiple AR layers, which is visually easy to distinguish. The participants also liked to view data by standing up, looking through, viewing from a certain angle, and adjusting their head orientation to analyze the AR layers. The participants took slightly more time to perform these two tasks than on physical monitors, but accuracy is better than tablets. On the tablet, when working with multiple graphs simultaneously, the graphs overlap each other. In interviews, participants mentioned that on the tablet, the graphs overlap, making it challenging to find the values when all graphs are on. The AbVD and ArVD helped to analyze data better in challenging visualizations such as viewing multiple graphs simultaneously and performing data analysis on extensive time-series data extending through AR. With some reasonable level of training in using the tablet+AR interface and a few improvements such as a grid or a movable slider to read the values better.

Takeaway ArVD and AbVD implementation

Some key takeaway from implementation is that it is not always about the number of UI operations we have to manipulate the data; it is about how concise they are to support the visualization. To elaborate on concise UI, we had several buttons for each function during the initial pilot studies. Then later, we modified the user interface to be more precise and self-explanatory. AR visualization in layers and focus+context view should appear native to the tablet, i.e., color and size similar to the tablet display. The main challenge was AbVD implementation is achieving transparency and enabling ArVD time-series data to move in sync with the tablet. Both challenges were overcome at one point after extensive trials. In AbVD, we changed the alpha value of Webviews and made changes to the code to make the background of the layers transparent. In ArVD, introducing a smaller axis to adjust the view precisely in focus+context display helped us mitigate the challenges.

Impact of Above display and Around display in participant perspectives

During the interview, we asked the participants how they felt about the display in terms of data analysis and data comprehension of BCI data. 40 participants felt that AbVD and ArVD interfaces created a positive impact in terms of data comprehension. The participants felt that time series is generic and can be easily applied to visualizations outside BCI. The participants felt that the interface addressed some core visualization challenges, such as viewing extensive time-series data and presenting the data in layers. The participants also felt that they could understand valence and arousal and how they are derived through the experiment with interface. The interview with neuroscience participants revealed that they could apply this interface to support data analysis in some areas of neuroscience.

Interviews with Expert Neuroscience Participants

We had 4 participants with neuroscience backgrounds, and during the interview, we asked them about some potential areas in neuroscience where our above display and around display interface can be used. They felt the interface could be applied in analyzing timelines to see cell structure changes for specific functions compared to others to see how it is affected and how it affects the other one. The AR layers could be changed to cell layers, for example, the retina, which has multiple layers of cells and add or remove the layers to see what happens. The graphs are generic and can be used in different applications in neuroscience, the axon elongation of the neurons, and see the cell body. Move the cell body through the axon and see different parts like the cell body and dendrites. Layering could be applied in analyzing the strength of connections between different agents and networks between agents. One participant felt the number of layers did not matter and provided a way to make it more precise for analyzing the values. The around display could be related to one application for pressure data visualization, which could help to pinpoint locations where pressure is more or less.

ArVD and AbVD has a potential to be used in interdisciplinary domains for presenting data

We had participants from different domains such as architecture, chemistry and interdisciplinary studies. The participants mentioned that ArVD has a positive impact when we probed them regarding their experience with ArVD and its potential benefits of integrating them with their domain. Participant P48 who is from interdisciplinary studies said that ArVD interface has a positive impact in terms of bias and the interface has a strength to be integrated to the interdisciplinary domains as social systems to present data to large population E.g Population and addiction statistics, Micro-regression, Macro-regression and insights about society. P48 further added, for patients in audiology how psycho-acoustic music helps calm nerves and those have particular waves data can be visualized in ArVD. When a music is heard, to identify the regions of the brain that are activated in response to music and its frequency in a specific epoch. One of the participants P37 from electrical engineering said that the interface can be used in electrical drawings that can make use of extended space especially in ArVD.

We believe our research contributed to hybrid interface research that explores the benefits of multiple interfaces to perform a task or to address a complex visualization i.e., presenting data recorded for longer duration and multiple related data. Our method to present complex visualizations using augmented display for better data understanding of data and better data analysis have the potential to overcome screen size limitations in conventional tablet display. Our user study provided substantial data to understand the tablet+ AR HMD better, which lacked in previous researches such as MARVIS[1], MIRIA[2], DesignAR[3] and Personal augmented reality for large displays by Satowski et al.[48]. In brain computer interface domain, our research bring valuable addition to immersive data analytics of BCI data and exploring different interfaces to visualize BCI data better.

The previous research in extending the displays with augmented reality from interactive surfaces such as tablets is explored in DesignAR, where the researchers created a 3D modeling workstation using tablets and augmented reality[3]. Due to the lack of standard tools to project multivariate data in augmented reality[64], visualizing graphs with large data with more than 5000 data points in our research was challenging to build and slow to render in AR. In ARTIV, we used 2D in augmented reality, and our AR display is through Webviews and it was faster to deploy on HoloLens 2.

The evidence that interactive surfaces such as tablets proved to be an excellent platform to explore extended displays in AR is seen in previous research MARVIS[1] and DesignAR[3]. The strong aspects of using the Microsoft Surface Pro 3 in ARTIV research are the detachable screen and touch interactions. The surface pro can be placed on the table, and touch interactions with the tablet are smooth to manipulate the data presented in the tablet and the AR. Augmented reality offers certain advantages to extended displays; one primary advantage is that it costs less space[4]. In ARTIV ArVD, we enlarged the time-series data to 12.5 feet, providing evidence that AR can help present extensive data without a sizeable physical display. Pavanatto et al.[4] conducted a user study that compared conventional displays against virtual displays in a user study to explore the benefits of virtual displays in terms of performance and productivity. In ARTIV, we compared the hybrid tablet+AR HMD interface with tablet-only conditions for understanding the data and performing data analysis tasks. Our results showed that extended displays are indeed helpful for visualization challenges due to screen size and the nature of data.

MARVIS[1] and Personal augmented reality for large interactive displays[48] did not have a user study that compares tablet+AR interface with physical monitors. MARVIS[1] and MIRIA[2] have expert user feedback to evaluate their interface. Our study is extensive and comprised of two domains BCI and Space syntax. Focus+context technique was explored in [58] and it was applied in MARVIS[1]. Comparative study of interfaces was performed in [4]. In our research we recruited 48 participants, and 4 among them were from neuroscience backgrounds(encouraged by [1, 2]). Our work is unique in terms of data type and visualization problem i.e., screen size limitation and our techniques i.e., Layering and focus+context to address the problem when compared to previous researches.

6.0.2 Contributions and related works

ARTIV-BCI compared to previous research that used tablet+AR

Overall, in ARTIV BCI, we created the extended AR displays above and around the tablet, using the focus+context method to present the data visualization to the user. Our interface differs from earlier relevant works such as MARVIS[1] by the scale of data presented in AR around the display and the number of AR layers above the display. MARVIS did not explore the interface specific for data but focused on techniques that demonstrate above, around, between displays visualization. As far as we know, no earlier research demonstrated a hybrid interface for exploring Brain Computer Interface data.

DesignAR [3] is another work that demonstrated tablet+AR for data visualization that motivated our research. When DesignAR mostly deals with 3D modelling using combined tablet and augmented reality, whereas our work is related to 2D visualization. Both MARVIS [1] and DesignAR [3] demonstrated tablet and AR can be used for data analysis.

Revisiting over-plotting and screen size limitation

The research problems of ARTIV-BCI are over-plotting and screen size. Reipschlager et al. [48] presented sub-trends from visualizations in a large interactive display using AR. MIRIA [2] also demonstrated the user trajectories in AR that extend from a large screen. A large screen might not always be a solution for displaying large visualization with thousands of data points and multiple related visualizations, such as different sub-trends from data. Urushiyama et al. [136] demonstrated that portable devices such as smartphones can extend their displays using another physical display to present focus region in the phone and off-screen contents. In [136], we still require another physical display. ARTIV-BCI demonstrated two techniques, 1) layering and 2) focus+context, that portrayed how AR can be used as an alternative to extend physical screens. The benefits are, however, not limited to two techniques. Several other techniques, such as 360-degree around the tablet display AR visualization, can be a potential future work.

Comparison of hybrid interface with conventional interface

Comparing conventional interfaces such as tablets and personal computers with a hybrid interface such as tablet+AR can measure the usability of a hybrid interface for a particular research problem. Pavanatto et al. [4] conducted a comparative study on hybrid, physical and virtual interfaces and measured the usability using task accuracy, time taken and perceived usability. Craig et al. [140] also compared two learning environments: tablet augmented reality and head-mounted displays. Our motivation to compare tablet+AR with a tablet-only interface is mainly from work by Pavanatto et al. [4]. Similar to [4], We conducted our interface evaluation in a lab, and the evaluation of AbVD and ArVD under real-world circumstances could be a potential future work.

Contributions to BCI research

In our research, we treat our dataset as a black box. The lack of sufficient pre-processing to reduce noise and algorithms to extract accurate valence and arousal values is acknowledged. Combining BCI with augmented reality has been demonstrated in [33, 34]. However, they are industry-specific applications that use live BCI signals to perform a task in AR applications or visualize BCI data. As far as we know, our research is the first to demonstrate BCI data visualization and exploration in a tablet+AR interface. Through our layering and focus+context technique, we inferred some benefits of AbVD and ArVD in identifying salient data points. There is scope for future work, such as large-scale artifact analysis for ERP data running for data recorded for a longer duration using focus+context and multiple artifact analysis using the layering technique.

6.0.3 Summary of Limitations

Grid or slider to read X and Y values:-

In the current implementation of AbVD, the user can only read the X and Y values by looking at the graph, adjusting the head orientation, and matching the X and Y values using the finger and identifying the values. In AbVD, participants felt that they should be given an option to toggle one or more layers on or off in all types of tasks. The participants felt that if there were a grid in each AR layer, it would be helpful to read the values.

Identifying values of salient data points that are located far away:-

In around display, the participants felt challenged to compare the value of a data point if the Y-axis is far. In the Around display AR interface, we provided three Y-axis, one on the tablet and the other two on both sides of the time-series data. If a data point is for the participant, either uses fingers to match the data point to the Y-axis or moved close to the data point and read the values. Hence in the above display AR interface, the number of layers and their overlapping caused some difficulties in reading X and Y-axis values. In ArVD, due to the size of the time series data, it was challenging for participants to read the Y-axis data points that are located far away.

Resolution of AR visualization in HoloLens 2:-

The resolution of AR in HoloLens is less when compared to a tablet, which posed some significant challenges in reading the values. The participants felt that wearing the headset for a long time caused some neck pain and ergonomic issues. The spacing between layers is mostly fine. However, participants felt that the spacing could be adjusted between the layers, which better suits the participant's height. The swipe feature is ruled out due to challenges in making the sync in visualization between tablet and WebViews when the user swipes the tablet to move the time series data.

Swipe accuracy due to touch sensitivity:-

In our current ArVD implementation we navigated the time-series by clicking on focus points in the tablet. We initially attempted to implement swipe feature to move the time-series data from the tablet, however touch sensitivity of tablet is more than Webviews where the portion of AR visualization is presented in HoloLens 2. Hence we are unable to achieve accurate swipe that places the accurate continuity of data in the AR from the tablet. To mitigate this we gave the participant to click on focus points to adjust the view of time-series and shift-left and shift-right feature to shift the data towards left or right from the tablet UI.

Methodology limitations

The duration of our study is longer due to combined BCI and Space Syntax experiments i.e., average of 2 hours and 30 minutes. Participants performed the experiments in both BCI and Space Syntax in the order after counterbalancing. In order to mitigate fatigue we requested the participants to inform the researchers if they need some break after each experiment for water, restroom or to simply remove the HMD and rest for sometime/take a walk before proceeding with other experiment. We acknowledge the limitations due to fatigue having conducted a study that comprised two different data i.e., BCI and Space Syntax. Our combined study comes under broader research perspective of ARTIV to answer research questions in future that evaluates whether the interface is suitable for a specific type of data or different types of data.

The primary indicators used in our research are task accuracy and time taken to complete the tasks. Both indicators helped us evaluate our interface's usability for specific tasks, i.e., correctness in identifying salient data points and time taken to accomplish the task. However, to measure data comprehension, many other indicators can be used along with task accuracy and time taken to measure comprehension e.g., Pavanatto et al. [4] visual attention and head orientations which we acknowledge as a limitation.

In our experiments, we asked the participants to perform the tasks seated except Group 3 in AbVD, where participants stood up and looked down at the AR layers. Our study is a lab based study, we kept the tablet flat on the surface and noted in observations if the participant moved from their position. However, we acknowledge that we did not have a scenario where the participant picked up the tablet, moved around and performed the task. We also did not have a scenario where the tablet screen is positioned in different viewing angles and see how the participants perceive the AbVD and ArVD visualization. Both scenarios could be areas of future work.

6.0.4 Future work

Hybrid interfaces have excellent scope for handling complex visualization challenges due to the screen limitations of physical monitors. During interviews, when we asked the participant if the hybrid interface (AbVD and ArVD) impacted the data analysis and data comprehension positively, 40 participants felt the hybrid interface positively impacted analyzing the data. The participants felt that if the user were given an option to switch between the tablet visualization and the AR visualization, it would help them get different perspectives. In terms of feature, If AbVD and ArVD interfaces are upgraded with features to adjust space between the layers, increase or decrease the font size, and switch colors that are more suitable for the user to view the data, it might further enhance the task accuracy and user experience. In AbVD interface adding a grid to AR layers to read the X and Y values better.

In ArVD, a movable Y-axis that can slide through the AR display is one future improvement that can be added to read X and Y values better when a data point is far. Another essential improvement to the ArVD interface is the precise swipe feature that could enable both tablet and AR to move the time series data in sync. One participant gave feedback for ArVD regarding a curved display for time series data. In Webviews, a curved display is possible with external assets that can bend the canvas. Curved AR display for longer duration time-series data is a possible future upgrade for ArVD. In the current setup, we use BCI data already processed in OpenVibe. There is also good scope to create visualizations using live data from OpenVibe, stream them to the interface, and create a live time-series visualization. In terms of BCI, evaluating AbVD and ArVD for a specific medical use cases for example long duration EEG data analysis for identifying seizure patterns in patients can explore the usability of interface even further. We did not evaluate tablet+AR in comparison with a pure virtual monitor setting which could potentially evaluate the benefits of data exploration in a tablet+AR interface versus AR only interface.

Chapter 7

Conclusion

In ARTIV BCI, we designed AbVD and ArVD interfaces for comprehending BCI data. We learned to develop a hybrid tablet+AR interface using design paradigms and earlier works that supported visualizing data using tablet and augmented reality. We successfully implemented two techniques in our interface, layering and focus+context techniques to present BCI data. We evaluated our AbVD and ArVD interfaces through within-participants study. Our results indicated significantly higher task accuracy in finding the salient data points in individual graphs presented on layers and extended view of time-series supported HA2 and HB2 hypotheses in AbVD and ArVD. In terms of time taken, Tablets took significantly lesser time than AbVD interface. Our qualitative data analysis indicated several areas of future work, limitations and lessons learnt during the development AbVD and ArVD. Overall, our research provides evidence that hybrid interfaces such as tablet+AR are beneficial for exploring BCI data. Our research also provided evidence that comparing a conventional display with a hybrid interface can lead to interesting findings in terms of the strengths and limitations of the interface in visualizing data. Our study that compared hybrid interface with conventional displays is beneficial in finding answers to how visualizing the data using layering and focus+context in AbVD and ArVD is better compared to a tablet-only interface. Our work can motivate future researchers to use tablet+AR in different domains to visualize complex data.

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Appendix A

Recruitment notice to students

Appendix A – Recruitment Notice for the Session

We are recruiting participants to take part in a research study to evaluate two different types of physical display enhancements using augmented reality – presenting supplementary content *around a tablet display* and presenting related content *above a tablet display*. We are exploring how effective these techniques are for exploring brain-computer interface (BCI) data and spatial analysis data. We are recruiting 48 individuals, both with and without prior experience using virtual or augmented reality headsets.

If you decide to participate in this research, you will be asked to visit the VR and graphics Lab (Mona Campbell, 4th floor) for two separate sessions, each lasting 60-90 minutes. During these sessions, you will complete information-seeking tasks involving a tablet device and augmented reality headset, complete short questionnaires, and an interview. Participating in the session is voluntary and you will receive an honorarium of 30 dollars in thanks for your participation.

If you are interested in participating, please contact Hariprashanth Deivasigamani (hr533370@dal.ca).

Figure A.1: Recruitment notice to students

Appendix B

Consent form for the participants

Appendix B – Consent form for the Session

DALHOUSIE UNIVERSITY

CONSENT FORM

Project title: Above and Around the tablet Information Visualizations in AR for BCI and Space Syntax.

Lead researchers: Ramanpreet Kaur, Faculty of Computer Science

Hariprashanth Deivasigamani, Faculty of Computer Science

Other researchers

Hubert (Sathaporn) Hu, Faculty of Computer Science

Dr. Derek Reilly, Faculty of Computer Science

Funding provided by: MITACS / Ericsson.

Introduction

We invite you to take part in a research study conducted by Hariprashanth Deivasigamani and Ramanpreet Kaur, who are students at Dalhousie University. Your participation is voluntary, and you may withdraw from the study at any time. Your academic (or employment) performance evaluation will not be affected by whether you participate. The study is described below.

The purpose of this study is to evaluate two types of tablet display enhancements made possible using an augmented reality (AR) headset—*around the display*, where contextual information is presented around a tablet's screen, and *above the display*, where layers of related data float above a tablet's screen. You will use these techniques to explore floorplan analysis(space syntax) data and brain-computer interface (BCI) data. Participants with background in Architectural, Neuroscience, Psychology and computer science preferred. Participants cannot have a diagnosis of colour blindness. No prior experience with augmented reality, BCI, or floorplan analysis is required to participate. Your participation will help us to better understand how to combine AR and tablet displays for data analysis.

If you decide to participate in this research, you will be asked to visit the VR and graphics Lab (Mona Campbell building, 4th floor) for two sessions. Each session will take 60-90 minutes. Sessions will begin with an overview of the study, this will include addressing any questions you may have. You will then be asked to perform a set of pre-defined tasks with BCI and floorplan datasets using two different interfaces, and to answer a brief questionnaire after each set of tasks. After all tasks are done, you will complete another brief questionnaire and answer a few interview questions.

Figure B.1: Consent form

There are no direct benefits for participating, but we might learn new things about interface design that may benefit others. There are no risks for participating in this research beyond feeling a bit of discomfort wearing the augmented reality headset. Unlike virtual reality headsets, augmented reality headsets are not known to trigger feelings of nausea.

Participants will receive an honorarium of 30 dollars as a token of appreciation. Participation in this research will be known only to the members of the research team. The identity of each participant will be kept confidential: no video or audio will be used in publication or stored in public data repositories, and any quotes used in publication will be identified only by participant ID. The informed consent form and all identifying research data (audio, video) will be kept in a secure location under confidentiality in accordance with University policy for three years post publication and then destroyed. Non-identifying data (task times, software logs, and questionnaire data) will be stored in a public data repository to support the integrity of our research findings.

In the event that you have any difficulties with, or wish to voice concern about, any aspect of your participation in this study, you may contact Catherine Connors, Director, Office of Research Ethics Administration at Dalhousie University's Office of Human Research Ethics for assistance at (902) 494-3423, or email: ethics@dal.ca.

Signature Page

Project Title: Above and Around the tablet Information Visualizations in AR for BCI and Space Syntax.

Lead Researcher: Hariprashanth Deivasigamani ,Faculty of Computer Science, hr533370@dal.ca
Ramanpreet Kaur, Faculty of Computer Science, rm216536@dal.ca

I have read the explanation about this study. I have been given the opportunity to discuss it and my questions have been answered to my satisfaction. ***I understand that a video recording of my interactions with the interface is necessary to participate in the study, but that this video will only be viewed by the researchers. I understand direct quotes of things I say may be used without identifying me.*** I agree to take part in this study. My participation is voluntary and I understand that I am free to withdraw from the study at any time.

time.

Name	Signature	Date

Figure B.2: Consent form(Cont)

Please provide an email address below if you would like to be sent a summary of the study results.

Email address: ________________

Note: The signature of a researcher or a witness is not required. Getting participants to sign two copies is not required, and in fact may compromise privacy if the participant copy is not stored securely.

Figure B.3: Consent form(Cont)

Appendix C

Task list for Above display and Around display

Above display Tasks –BCI

Training Tasks

Training Tasks for Above Display, BCI

Remember to “think aloud” as you complete each task.

1. Notice that different types of data are presented in separate layers. How many layers do you see, and what data is presented on each layer?
2. Individual layers can be toggled off and on. Toggle on the F3 and F4 layers and toggle off the valence and arousal layers
3. Select the Beta value F3 and F4. Do you notice the values change in the F3 and F4 layers?
4. Observe and report the Beta value for F3 at 1200 epochs. Tell me the Beta value for F4 at the same epoch.
5. Toggle on the valence and arousal layers (all layers should now be on). Stand up and look down directly above the tablet through all the layers and state the values of valence and arousal at 1800 epochs.
6. Sit down again. From seated, find a viewing angle where the layers don’t overlap. Identify the highest peak in each layer and state what the frequency and epoch values are.

Training Tasks for Physical Monitor, Around Display, BCI

1. Notice that different types of time series data are presented in the tablet. How many time series graphs do you see, and what data is presented on graph?
2. Toggle off the F3 and F4 graphs.
3. Observe and report the valence and arousal values at 1000 epoch.
4. Toggle on the F3 and F4 graphs and toggle off the valence and arousal graphs.
5. Observe and report the Alpha F3 and Alpha F4 values at 1000 epoch.
6. Switch to Beta F3 and Beta F4.
7. Observe and report the Beta F3 and Beta F4 values at 1000 epoch.
8. Toggle on all the layers and report the arousal value at 1500 epoch.

Figure C.1: Training tasks for Above display and physical monitors

Task Sets

Note: for the Above Display Condition, we will follow this protocol: Task group 1 will be done while seated, group 2 will be done while seated and looking at the layers from an angle in which layers are non-overlapping, group 3 will be done while standing and looking down at the layers, and group 4 will be done using the participant's own preferred set of approaches.

Task Set 1

Group 1:

1. Toggle on the valence layer and toggle off all other layers.
2. Observe and report the valence value at 1400 epochs.
3. Toggle off the valence layer and toggle on the F4 layer.
4. Observe and report the Alpha F4 value at 1400 epoch.
5. Select the Beta F4 value.
6. Observe and report the Beta F4 value at 1400 epochs.
7. Which value was higher for F4: Alpha or Beta?
8. Toggle off the F4 layer and toggle on the F3 layer.
9. Observe and report the Alpha F3 value at 1400 epochs.
10. Select the Beta F3 value.
11. Observe and report the Beta F3 value at 1400 epochs.
12. Which value was higher for F3: Alpha or Beta?

Group 2

Instructions (Above Display condition): From seated, find a viewing angle where the layers don't overlap.

1. Toggle on all the layers.
2. Select the Alpha F3 and Alpha F4 values.
3. Observe and report the arousal value at 1500 epochs.
4. Observe and report the valence value at 1500 epochs.
5. Observe and report the Alpha F3 value at 1500 epochs.
6. Observe and report the Alpha F4 value at 1500 epochs.
7. Which Alpha value was higher: F3 or F4?

Figure C.2: Task-set 1 Above display

Group 3 :

Instructions (Above Display condition): Stand up and look down directly above the tablet through all the layers

1. Toggle on all the layers.
2. Switch to Beta F3 and Beta F4
3. Observe and report the arousal value at 800 epoch.
4. Observe and report the valence value at 800 epoch.
5. Observe and report the Beta F3 value at 800 epoch.
6. Observe and report the Beta F4 value at 800 epoch.
7. Which beta value was higher: F3 or F4?

Group 4 :

Instructions (Above Display condition): Use any approaches you wish to accomplish the following tasks. You can toggle one or more layers ON or OFF, and view data from any angle while seated or standing.

1. Observe the arousal value at 1800 epochs and report the valence value at the same point.
2. Observe and report the Alpha F3 value at 1800 epochs
3. Observe and report the Alpha F4 value at 1800 epochs.
4. Observe and report the Beta F3 value at 1800 epochs.
5. Observe and report the Beta F4 value at 1800 epochs.
6. Which value was higher in F3: Alpha or Beta?
7. Which value was higher in F4: Alpha or Beta?

Figure C.3: Task-set 1 Above display Cont.

Baseline task for above display (Merged layer):

Instructions: The participant can use the tablet normally the way they do. No specific instructions for head orientation or resting position.

Task Set 2

Group 1:

1. Toggle on valence graph and toggle off the remaining graphs
2. Observe and report the valence value at 1600 epoch.
3. Toggle off the valence graph and toggle on the F4 graph
4. Observe and report the value of Alpha F4 value at 1600 epoch.
5. Switch to Beta F4.
6. Observe and report the Beta F4 value at 1600 epoch.
7. Which value was higher in F4: Alpha or Beta?
8. Toggle off the F4 graph and Toggle on the F3 graph.
9. Observe and report the Alpha F3 value at 1600 epoch.
10. Switch to Beta F3.
11. Observe and report the Beta F3 value at 1600 epoch.
12. Which value was higher in F3: Alpha or Beta?

Group Two :

1. Toggle all the graphs on.
2. Switch to Alpha F3 and Alpha F4.
3. Observe and report the arousal value at 1700 epoch.
4. Observe and report the valence value at 1700 epoch.
5. Observe and report the Alpha F3 value at 1700 epoch.
6. Observe and report the Alpha F4 value at 1700 epoch.
7. Which alpha value was higher: F3 or F4?

Figure C.4: Task-set 2 Above display

Group Three :

1. Switch to Beta F3 and Beta F4.
2. Observe and report the arousal value at 600 epochs.
3. Observe and report the valence value at 600 epochs.
4. Observe and report the Beta F3 value at 600 epochs.
5. Observe and report the Beta F4 value at 600 epochs.
6. Which beta value was higher: F3 or F4?

Group Four (Accomplish in the participant's own way):

Instructions: Use any approaches you wish to accomplish the following tasks. You can toggle one or more layers ON or OFF, and view data from any angle while seated or standing.

1. Observe the arousal value at 900 epochs and report the valence value at the same point.
2. Observe and report the Alpha F3 value at 900 epochs
3. Observe and report the Alpha F4 value at 900 epochs.
4. Observe and report the Beta F3 value at 900 epochs.
5. Observe and report the Beta F4 value at 900 epochs.
6. Which value was higher in F3: Alpha or Beta?
7. Which value was higher in F4: Alpha or Beta?

Figure C.5: Task-set 2 Above display Cont.

Around display tasks - BCI

Training Tasks for Around Display, BCI

Remember to “think aloud” as you complete each task.

1. Notice the type of data presented in tablet. What type of data do you see?
2. Click on zoom in button and click on 4500 epoch from the small axis below the time series graph
3. Click on 2500 epoch from the smaller axis below the tablet
4. Observe the data presentation extends from both sides of the tablet. Report the type of data.
5. Click on shift left twice and report your observation.
6. Click on shift right twice and report your observation.
7. Observe a highest peak in the time series data between 0 to 4500 epoch and using the X and Y axis report its value.
8. Click on arousal button
9. Click on 3000 epoch from the smaller axis.
10. Observe the number of peaks with arousal value more than 5 across Y-axis between the range 2000 and 5000 epochs across the X-axis. Report the epoch intervals between which the values can be seen.

Training tasks for physical monitors, Around display, BCI:-

1. Observe and tell what data is displayed on the tablet and how is it represented.
2. Click on zoom in and click on 4500 from the small axis below the time series graph
3. Click on 2500 from the smaller axis.
4. Swipe right using the finger and report the valence value at 1000 epoch
5. Click on shift left twice. Report your observation.
6. Click on shift right twice. Report your observation.
7. Click on arousal button
8. Swipe left and report the arousal value at 4000 epochs

Figure C.6: Training tasks for Around display and physical monitors

9. Observe and report the arousal peaks above 5 in the time series data between 4000 to 4500 epochs and using the X and Y axis.
10. Click on 3000 epoch from the smaller axis.
11. Observe the number of peaks with arousal value more than 5 across Y-axis between the range 2000 and 5000 epochs across the X-axis. Report the epoch intervals between which the values can be seen.

Figure C.7: Training tasks for Around display and physical monitors Cont.

Task sets:-

Task set 1

Note: For Around Display we follow this protocol. For group 1 the participants are guided through the approaches step by step to finish each task and for group 2 the participants can use their own set of approaches to accomplish each task.

Group 1:

Instructions(Around Display condition): Use the exact focus points in the smaller axis as instructed by the researcher to adjust the view of the time series data.

1. Click on zoom in button. Switch to valence.
2. Click on 3500 epochs from the smaller axis.
3. Observe and report the extent of the time series data.
4. Click on 4000 epochs from the smaller axis.
5. Observe and report the number of peaks with valence value more than 5 across Y-axis between the range 2000 and 5000 epochs across the X-axis.
6. Observe and report the closest epoch intervals between which valence value more 5 can be seen.
7. Click on 5500 from the smaller axis.
8. Click on shift right twice.
9. Observe and report the valence value at 4500 epochs.
10. Click on 500 from the smaller axis.
11. Click on shift left twice.
12. Observe and report the number of points the valence drops to 0 over Y-axis between the range 0 and 3500 epochs over X-axis.
13. Observe and report the closest epoch intervals between which the valence value of 0 can be seen.
14. Click on 7000 epochs from the smaller axis.
15. Between 5500 to 6000 epochs, observe and report many valence peaks can you see between the values between 3 to 6.
16. Observe and report the closest epoch intervals between which the valence values of range 3 to 6 can be seen.

Figure C.8: Task-set 1 Around display

17. Observe the whole time series data and identify a point where valence value is above 8.
18. Observe and report the closest epoch intervals between which the values above 8 can be seen.
19. Click on arousal button
20. Did you observe the time series data changed from valence to arousal? Yes or No
21. Click on 4000 epochs from the smaller axis.
22. Observe and report the arousal values at 5000 epoch.

Group 2:

Instructions (Around Display condition): Use your own set of approaches to accomplish the tasks

1. Switch to valence.
2. Observe and report the valence value at 4000 epochs.
3. Switch to arousal.
4. Click on 3500 epochs from the smaller axis.
5. Observe and report the number of points with arousal values more than 5 across Y-axis between the range 2000 and 5000 epochs across X-axis.
6. Observe and report the epoch intervals between which the arousal values above 5 can be seen.
7. Observe and report the arousal values at 5000 epoch.
8. Observe and report number of points the arousal dropped to 0 over Y-axis between the range 1000 and 1500 epochs over X-axis.
9. Observe and report the closest epoch intervals between which the arousal values of 0 can be seen
10. Click on 7000 from the smaller axis
11. Observe and report the number of points the arousal value between 4 and 7 can be seen between the range of 5500 to 6000 epochs.
12. Observe and report the closest epoch intervals between which the arousal values of range 4 to 7 can be seen.
13. Identify a point where arousal is above 8 and report the closest epoch intervals between which arousal value above 8 can be seen.

Figure C.9: Task-set 1 Around display Cont.

Baseline tasks for around display

Task set 2: :

Group 1:: -

Instructions: (Physical monitor condition) Use your fingers to swipe left or swipe right whenever necessary to navigate through the time series data whenever needed.

1. Click on zoom in button.
2. Click on 2000 epochs from the smaller axis.
3. Observe and report the extent of the time series data.
4. Click on 3000 epochs from the smaller axis.
5. Observe and report the number of peaks with valence value more than 5 across Y-axis between the range 2500 and 5500 epochs across the X-axis.
6. Observe and report the closest epoch intervals between which valence value more 5 can be seen.
7. Click on 5000 from the smaller axis.
8. Click on shift right twice.
9. Observe and report the valence value at 5500 epochs.
10. Click on 1000 from the smaller axis.
11. Click on shift left twice.
12. Observe and report the number of points the valence drops to 0 over Y-axis between the range 500 and 4000 epochs over X-axis.
13. Observe and report the closest epoch intervals between which the the valence value of 0 can be seen.
14. Click on 6500 epochs from the smaller axis.
15. Between 6000 to 7000 epochs, observe and report many valence peaks can you see between the values between 3 to 6.
16. Observe and report the closest epoch intervals between which the valence values of range 3 to 6 can be seen.
17. Observe the whole time series data and identify a point where valence value is above 7.

Figure C.10: Task-set 2 Around display

18. Observe and report the closest epoch intervals between which the values above 7 can be seen.
19. Click on arousal button
20. Did you observe the time series data changed from valence to arousal? Yes or No
21. Click on 5000 epochs from the smaller axis.
22. Observe and report the arousal values at 5500 epoch.

Group 2:

Instructions: (Physical monitor condition) Use your own set of approaches to complete the tasks

1. Switch to valence.
2. Observe and report the valence value at 4500 epochs.
3. Switch to arousal.
4. Click on 4000 epochs from the smaller axis.
5. Observe and report the number of points with arousal values more than 5 across Y-axis between the range 2500 and 5500 epochs across X-axis.
6. Observe and report the epoch intervals between which the arousal values above 5 can be seen.
7. Observe and report the arousal values at 6000 epoch.
8. Observe and report number of points the arousal dropped to 0 over Y-axis between the range 1500 and 2000 epochs over X-axis.
9. Observe and report the closest epoch intervals between which the arousal values of 0 can be seen
10. Click on 6500 from the smaller axis
11. Observe and report the number of points the arousal value between 4 and 7 can be seen between the range of 6000 to 7000.
12. Observe and report the closest epoch intervals between which the arousal values of range 4 to 7 can be seen.
13. Identify a point where arousal is above 7 and report the closest epoch intervals between which arousal value above 7 can be seen.

Figure C.11: Task-set 2 Around display Cont.

Appendix D

Questionnaire for Hololens familiarity and Participant background

Familiarity with the HoloLens Study Questionnaire

1. I classify my level of knowledge in Augmented Reality/Virtual Reality/Mixed Realityas:

Mark only one oval.

Extremely Familiar	Moderately Familiar	Somewhat Familiar	Slightly Familiar	Unfamiliar
○	○	○	○	○

2. I have experience with Virtual Reality games or other VR apps using a headset(Oculus, HTC Vive etc).

Mark only one oval.

- Yes
- No

3. I have used some augmented reality applications before e.g Pokemon Go

Mark only one oval.

- Yes
- No

4. Have you used Microsoft Hololens or another AR HMD before ?

Mark only one oval.

- Yes
- No

Figure D.1: Hololens familiarity questionnaire

Questionnaire for Above the Display and Physical Monitors for Space Syntax:

Above and Around the Display AR data visualization of BCI and Space Syntax

Study Questionnaire

1. What is yourgender:

   Mark only one oval.

	Female	Male	Other

Other: ____________________

2. Gender: How do you identify yourself?

   Mark only one oval.

Man	Woman	Non-Binary	Prefer to Describe	Other

Prefer to describe yourself as below Other:

____

Figure D.2: Participant background questionnaire

3. Your level of education

Mark only one oval.

High School	Bachelors	Masters	PhD/PDF	Other
O	O	O	O	O

Other: ______________________

4. Your current designation

Mark only one oval.

Student	Professor	Other
O	O	O

Other: ______________________

Figure D.3: Participant background questionnaire cont

Appendix E

Above display - Interface and post condition questionnaire

Above display tasks for BCI

For all statements below mark the circle that most closely matches your level of agreement/disagreement. Mark only one circle for each statement.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

1. I could see all four time series graphs clearly in the augmented reality (AR) configuration.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

2. It was straightforward to interact with buttons on the tablet

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle

3. It was straightforward to isolate layers using the toggle feature

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure E.1: Above display

4. It was easy to determine the X and Y values of the plotted data using the X and Y-axis ticks present in the layers.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

5. It was useful to view layers at an angle such that each layer did not overlap.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

6. It was useful to view multiple layers in an integrated way by looking at them from above.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle

7. The layout and alignment of individual AR layers above the tablet was appropriate for performing the tasks

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Figure E.2: Above display cont.

Mark only one circle.

8. It was useful to change my position and orientation relative to the layers to achieve different perspectives.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

9. Completing the tasks helped me understand how alpha and beta contribute to the calculation of valence and arousal

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

10. I can imagine using this type of visualization setup to explore data in school or at work

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

11. I would recommend this type of visualization setup to my peers for data exploration

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Figure E.3: Above display cont.

Physical monitor tasks for BCI – Above Display

1. I could see all four time series graphs clearly on the tablet.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

2. It is straightforward to interact with the buttons on the tablet

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

3. It is straightforward to isolate layers using the toggle feature

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

4. It was easy to determine the X and Y values of the plotted data using the X and Y-axis ticks present in the graphs.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure E.4: Above display - Physical monitors cont.

5. It was useful to view multiple graphs in an integrated view on the tablet.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

6. Toggling off one or more graphs is useful compare graphs in a way the other graphs did not overlap

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

7. The layout and alignment of graphs on the tablet was appropriate for performing the tasks

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

8. Completing the tasks helped me understand how alpha and beta contribute to the calculation of valence and arousal /

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Figure E.5: Above display - Physical monitors cont.

9. I can imagine using this type of visualization setup to explore data in school, at work or home

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

10. I would recommend this type of visualization setup to my peers for data exploration

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Figure E.6: Above display - Physical monitors cont.

Post condition questionnaire (Above display and Physical monitor)

In the following section are statements that ask you to compare the two display conditions you have just completed: *AR* (layers presented above the tablet display) and *tablet* (all layers presented on the tablet display). For each aspect listed below, mark the circle that most closely corresponds to your opinion.

1. Visually distinguishing different layers .

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

2. Determining X and Y values at a given point for a single layer.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

3. Toggling layers on and off.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

Figure E.7: Above display - Post condition questionnaire

4. Viewing multiple layers together.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better

Mark only one oval.

5. Observing changes when switching between Alpha and Beta data.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better

Mark only one oval.

6. Understanding that valence and arousal are derived from F3 and F4 values.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better

Mark only one oval.

7. Keeping track of individual layers.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better

Mark only one oval.

Figure E.8: Above display - Post condition questionnaire cont.

8. Comparing two layers at a specific epoch.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

9. Finding data peaks in a layer.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

10. Completing tasks efficiently.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

11. Completing tasks accurately.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one circle.

12. Determining X and Y values at a given point.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Figure E.9: Above display - Post condition questionnaire cont.

Appendix F

Around display - Interface and post condition questionnaire

Around display tasks for BCI

For all statements below mark the circle that most closely matches your level of agreement/disagreement. Mark only one circle for each statement.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Form link:

https://docs.google.com/forms/d/1rT9gPg-nwfIYGlPYpjHk5hdXrBPHfko9SNRZZTy5KnA/edit

1. I could see the large time series data clearly stretching from both sides of the tablet after clicking on zoom in.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

2. The smaller axis is useful to navigate through the time series graph.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Figure F.1: Around display - Interface questionnaire

Mark only one circle.

3. The shift left and shift right buttons are useful to adjust the time series graph towards left and right.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

4. It is straightforward to isolate buttons on the tablet.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

5. The Zoom out function is useful to shrink the time-series data.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

6. The zoom in function is useful to extend the time series data beyond physical screen on the tablet.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure F.2: Around display - Interface questionnaire cont.

7. It was easy to determine X and Y values of the data using the X and Y axis present in tablet and AR layer

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one oval.

8. The layout and alignment of large time series data in around display was appropriate for performing the tasks

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

9. I could change the whole time series visualizations in the around display by clicking from the tablet

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one oval.

10. Completing the tasks helped me understand the valence and arousal data.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure F.3: Around display - Interface questionnaire cont.

11. I can imagine using this type of visualization setup to explore data in school and at work

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

12. I would recommend this type of visualization setup to my peers for data exploration

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure F.4: Around display - Interface questionnaire cont.

Physical monitor tasks for BCI – Around Display

For all statements below mark the circle that most closely matches your level of agreement/disagreement. Mark only one circle for each statement.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

1. I could see the large time series data clearly on the tablet after clicking on zoom in.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

2. The smaller axis is useful to navigate through the time series graph.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

3. The shift left and shift right buttons are useful to adjust the time series graph towards left and right.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure F.5: Around display Physical monitors - Interface questionnaire

4. It is straightforward to isolate buttons on the tablet

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

5. The Zoom out function is useful to shrink the time-series data.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

6. The zoom in function is useful to extend the time series data in tablet

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

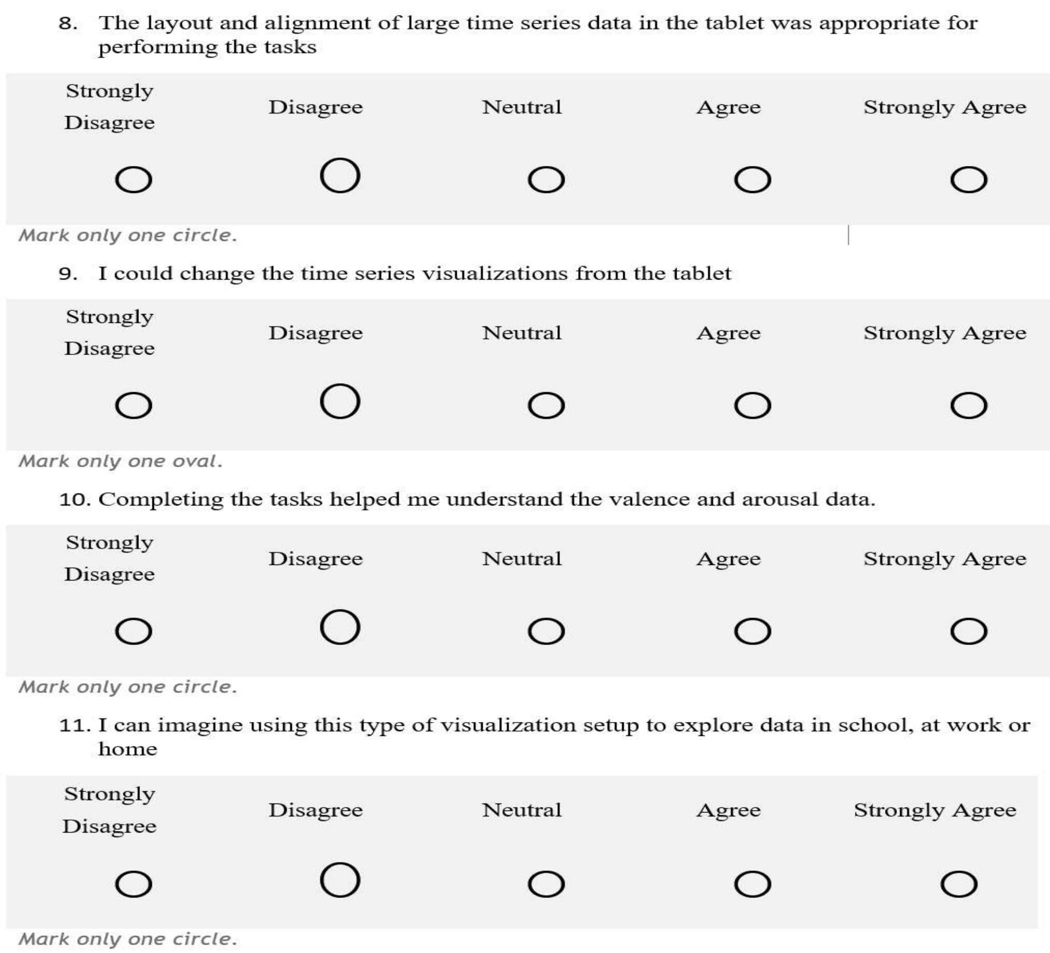
Mark only one circle.

7. It was easy to determine X and Y values of the data using the X and Y axis present in tablet.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one oval.

Figure F.6: Around display Physical monitors - Interface questionnaire cont.



8. The layout and alignment of large time series data in the tablet was appropriate for performing the tasks

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

9. I could change the time series visualizations from the tablet

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one oval.

10. Completing the tasks helped me understand the valence and arousal data.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

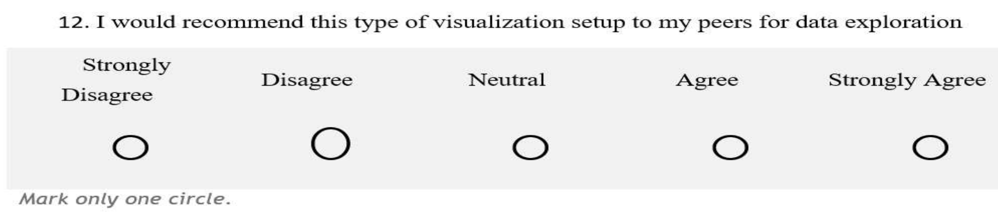
Mark only one circle.

11. I can imagine using this type of visualization setup to explore data in school, at work or home

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure F.7: Around display Physical monitors - Interface questionnaire cont.



12. I would recommend this type of visualization setup to my peers for data exploration

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure F.8: Around display Physical monitors - Interface questionnaire cont.

Post condition questionnaire (Around display and Physical monitors)

In the following section are statements that ask you to compare the two display conditions you have just completed: *AR* (layer around the tablet display) and *tablet* (all layers presented on the tablet display). For each aspect listed below, mark the circle that most closely corresponds to your opinion.

1. Navigating through the time series data

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

2. Determining X and Y values at a given point of the time series data.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

3. Zoom in and view the large time series data

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

Figure F.9: Around display - Post condition questionnaire

4. Observing changes when switching the time series graph and seeing the whole time series data clearly

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

5. Viewing a large time series data without the edges cut due to screen size.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

6. Understanding the valence and arousal values.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

7. Shift left and right of the time series data.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

Figure F.10: Around display - Post condition questionnaire cont.

8. Finding values between certain range in X and Y axis

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

9. Completing tasks efficiently.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one oval.

10. Completing tasks accurately.

AR Clearly Better	AR Slightly Better	AR and Tablet are Equal	Tablet Slightly Better	Tablet Clearly Better
○	○	○	○	○

Mark only one circle.

Figure F.11: Around display - Post condition questionnaire cont.

Appendix G

System Usability Scale(SUS)

System usability questionnaire

1. I think that I would use this system frequently

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

2. I found this system unnecessarily complex

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

3. I thought the system was easy to use

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

4. I think that I need support of technical person to complete the tasks

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

5. I found various functions in the system easy to use

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
○	○	○	○	○

Mark only one circle.

Figure G.1: System usability questionnaire

6. I thought there was too many inconsistencies in the system

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Mark only one circle.

7. I would imagine that most people would learn to use this system quickly

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Mark only one circle.

8. I found the system cumbersome to use

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Mark only one circle.

9. I felt very confident using the system

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Mark only one circle.

10. I needed to learn a lot of things before I could get going with the system

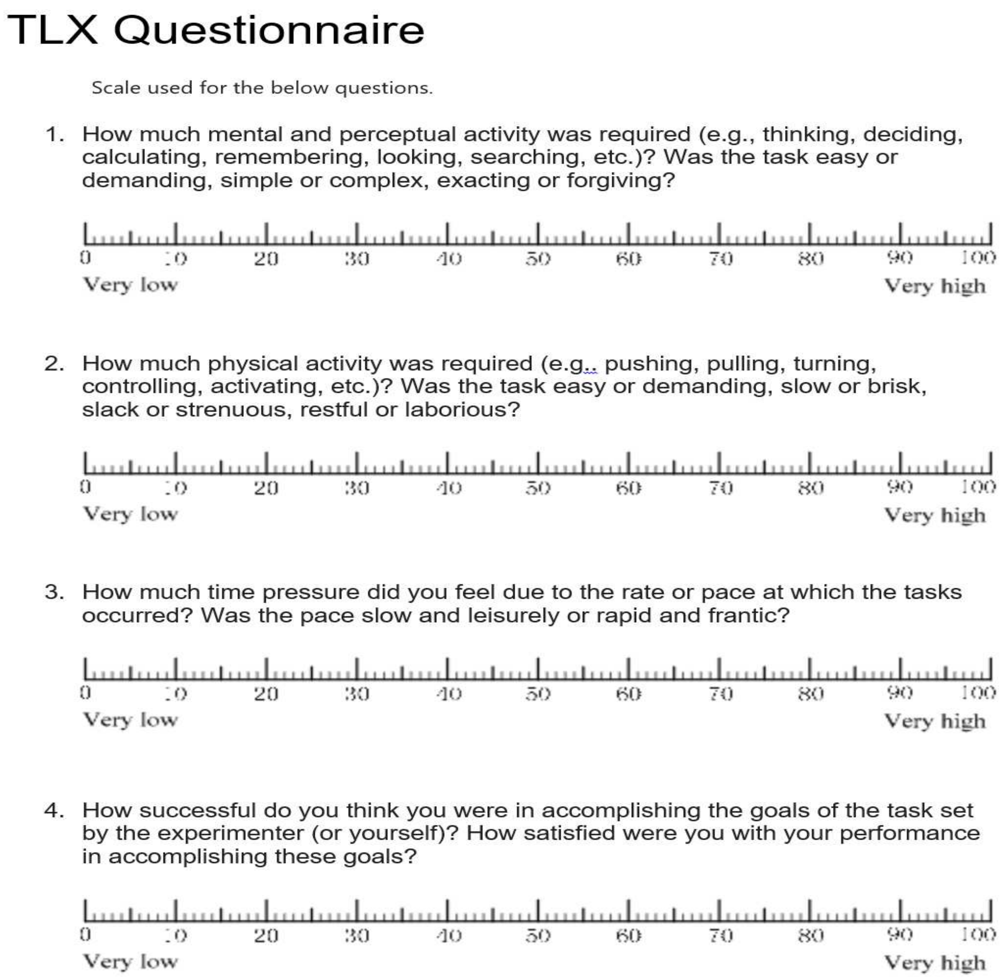
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Mark only one circle.

Figure G.2: System usability questionnaire cont.

Appendix H

Task Load Index(NASA-TLX)



TLX Questionnaire

Scale used for the below questions.

1. How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?

0 10 20 30 40 50 60 70 80 90 100

Very low Very high

2. How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

0 10 20 30 40 50 60 70 80 90 100

Very low Very high

3. How much time pressure did you feel due to the rate or pace at which the tasks occurred? Was the pace slow and leisurely or rapid and frantic?

0 10 20 30 40 50 60 70 80 90 100

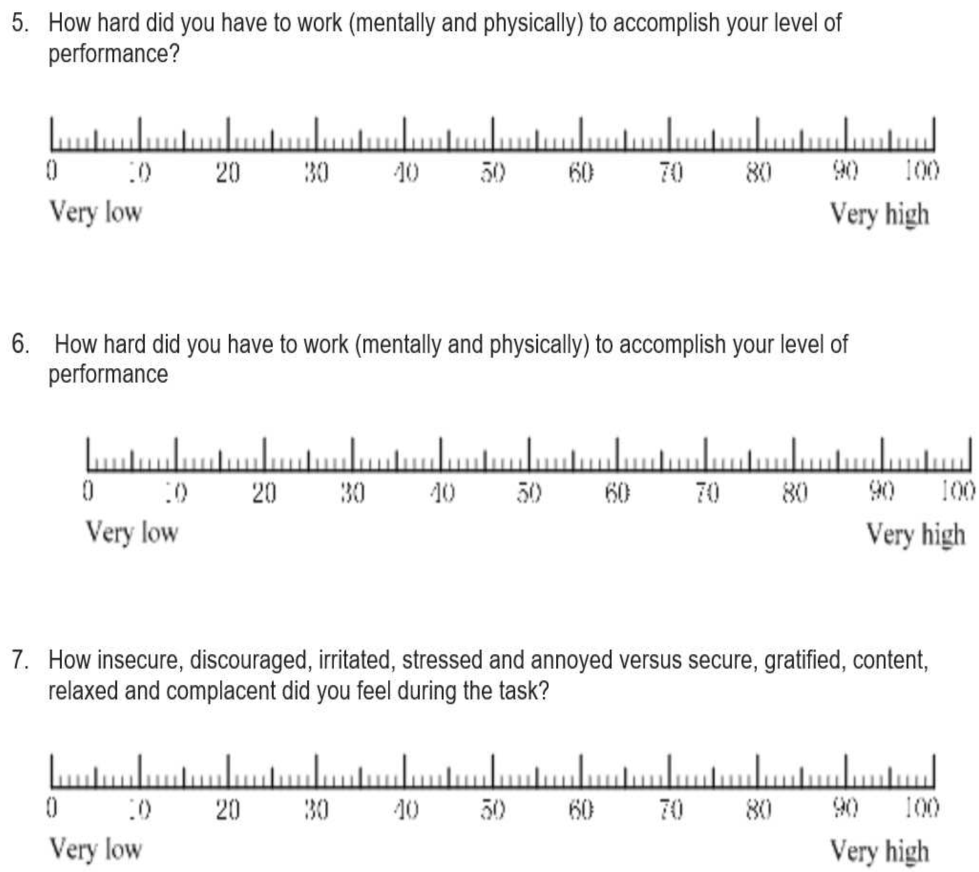
Very low Very high

4. How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

0 10 20 30 40 50 60 70 80 90 100

Very low Very high

Figure H.1: NASA-TLX questionnaire



5. How hard did you have to work (mentally and physically) to accomplish your level of performance?

0 10 20 30 40 50 60 70 80 90 100
Very low Very high

6. How hard did you have to work (mentally and physically) to accomplish your level of performance

0 10 20 30 40 50 60 70 80 90 100
Very low Very high

7. How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

0 10 20 30 40 50 60 70 80 90 100
Very low Very high

Figure H.2: NASA-TLX questionnaire cont.

Appendix I

Debriefing and interview

Debriefing and Interview

Our study involves evaluating interfaces with or without Augmented Reality by analyzing the various aspects of how the participants interact with the interfaces.
In this research through the data collected, we will analyze that how the information visualizations across different interfaces with or without AR for both BCI (Brain Computer Interface) and Space Syntax data visualization impact on data analysis from the user's perspective.
May I have your consent to record the audio for the interview?

1. How is your overall experience with the study?
2. Do you have any preference which domain works best for this setup – Space Syntax or BCI. Why?
2. Do you have any suggestions for improvement for both space syntax and BCI?
3. What were the interesting or engaging design aspects of this setup for both BCI and Space Syntax.
4. What did you learn about AR (Augmented Reality) today through our study?
5. In terms of data analysis and comprehension do you think above and around display has a positive impact or negative impact? Why?
5. What upgrades would you like to see in future is this setup?
6. Do you have any question for us?

Figure I.1: Debriefing and interview

Appendix J

Checklist for study

Checklist:

- Collect the consent forms from the participants.
- Brief the participants about the study “This research is conducted to evaluate the understanding of Brain Computer Interface and Space syntax across various interfaces with and without Augmented Reality. You will be performing few tasks wearing the HoloLens. We will record video and audio data for research purpose.
- Keep the HoloLens and Tablet always on charge if the participant has not arrived.
- The tablet should be on charged during the study as well.
- The HoloLens volume should be “0” and the brightness should be 80.
- As the participants fill the contact tracing form. Make sure the pens are sanitized.
- Make the participants watch video for Space syntax and BCI.
- Place the tasks list for the participants. Check the sheet to check which Group is assigned to the participant.
- Make sure these things are up and running.
  - Video recording in the HoloLens.
  - HoloLens application in the laptop to see what the participant is looking at.
  - HoloLens are charged and backup HoloLens is also there.
  - Ask the participants to think a loud.
- Make sure to collect the logs once the tasks are completed. Place the logs in the designated folder for each domain- Space Syntax and BCI.
  - Physical Monitor Around the Display.
  - AR Around the Display.
  - Physical Monitor Above the Display.
  - AR Above the Display.
- Collect logs from HoloLens and Tablet.
- Keep the questionnaires ready for the participants.
- Audio record the interviews.

Figure J.1: Study checklist

Appendix K

Participants diversity

Participant	Gender	AR familiarity	Participan	Gender	AR familiarity
P1	Female	Somewhat familiar	P25	Male	Somewhat familiar
P2	Male	Somewhat familiar	P26	Male	Somewhat familiar
P3	Male	Somewhat familiar	P27	Male	Moderately familiar
P4	Male	Somewhat familiar	P28	Female	Somewhat familiar
P5	Female	Moderately familiar	P29	Male	Somewhat familiar
P6	Female	Somewhat familiar	P30	Male	Somewhat familiar
P7	Male	Moderately familiar	P31	Female	Somewhat familiar
P8	Male	Moderately familiar	P32	Female	Unfamiliar
P9	Female	Moderately familiar	P33	Male	Unfamiliar
P10	Female	Slightly familiar	P34	Male	Somewhat familiar
P11	Male	Slightly familiar	P35	Male	Moderately familiar
P12	Female	Slightly familiar	P36	Female	Somewhat familiar
P13	Male	Somewhat familiar	P37	Female	Slightly familiar
P14	Female	Unfamiliar	P38	Male	Slightly familiar
P15	Male	Unfamiliar	P39	Female	Somewhat familiar
P16	Male	Somewhat familiar	P40	Male	Somewhat familiar
P17	Male	Somewhat familiar	P41	Female	Slightly familiar
P18	Male	Somewhat familiar	P42	Male	Moderately familiar
P19	Male	Unfamiliar	P43	Male	Moderately familiar
P20	Female	Moderately familiar	P44	Female	Slightly familiar
P21	Male	Moderately familiar	P45	Female	Slightly familiar
P22	Female	Slightly familiar	P46	Male	Somewhat familiar
P23	Female	Slightly familiar	P47	Male	Somewhat familiar
P24	Male	Moderately familiar	P48	Female	Somewhat familiar

Figure K.1: Participants diversity