# ICoN: Immersive Computational Notebook for Data Science

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# ICoN: Immersive Computational Notebook for Data Science

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## ABSTRACT

Computational notebooks are widely used in data science, offering an interface that integrates code, documentation, visualizations, and data within a single environment. However, as data analysis becomes increasingly complex, the traditional WIMP (Windows, Icons, Menus, Pointers) interface faces limitations in supporting advanced, embodied workflows. To address this, we initially adapted the computational notebook into the immersive environment to leverage the embodiment and immersiveness provided by immersive technologies. While our adoption of computational notebooks in immersive environments improved navigation performance, their standard interfaces were less effective, which required extensive text input for tasks such as data transformation and visualization. To overcome these challenges, we initially explored embodied data transformation, focusing on gesture-based, direct data manipulation within immersive environments. Embodied data transformation reduced cognitive load, enabling more intuitive data analysis without extensive text input and programming expertise. Building on these successful explorations, we developed ICoN, a system that integrates immersive computational notebooks, embodied data transformation, and visualization within a unified workspace. Through controlled comparisons of desktop vs. VR and separated vs. unified workspaces, we found that ICoN not only improves navigation performance but also enables intuitive data transformation and visualization capabilities. However, despite ICoN's potential, the organizational strategies where execution order plays an important role in immersive environments remain underexplored. Our next research addresses this gap by examining how users spatially arrange and interact with computational notebooks in immersive contexts. In a user study, participants favored organizing their work in half-cylindrical layouts and engaged more frequently in non-linear analysis compared to traditional setups. This shift suggests that immersive environments encourage new approaches to managing data science workflows, leading to a more flexible and efficient use of computational notebooks. Yet, general limitations, such as scalability, must be addressed for ICoN to be applied to real-world, complex data analysis scenarios, where tasks are performed over longer periods and with larger datasets. Manually adjusting large notebooks

for different tasks can be time-consuming and exhausting. To overcome these challenges, we introduced organizational guidance, which enables the system to assist analysts in building well-defined structures with consistent spacing and alignment. In our user study, we found that organizational guidance significantly improved the effectiveness of constructing large-scale analyses within immersive computational notebooks. By enabling participants to quickly reorganize their workspace, the system facilitated faster initiation of analysis. To isolate the effect of organizational guidance, we annotated specific cells in the study to highlight embedded structural patterns, helping participants focus on organization rather than code comprehension. However, in real-world analysis, the process often involves a sensemaking process, such as understanding the underlying execution logic, which remains necessary even with guidance. As a result, navigating large, immersive spaces remains inevitable for performing large-scale analyses. We envision incorporating lens techniques commonly used in the field of visualization, allowing analysts to closely inspect small or detailed data elements, and employing near-far proxies that reveal different levels of information based on the distance between the analyst and the target content.

# ICoN: Immersive Computational Notebook for Data Science

Sungwon In

## GENERAL AUDIENCE ABSTRACT

Computational notebooks are commonly used in data science tools that combine code, notes, graphs, and data in one place. However, as data analysis becomes more complex, traditional computer interfaces (which rely on windows, icons, menus, and pointers) struggle to support advanced tasks. To improve this, we integrated the computational notebook into virtual reality (VR) to leverage the immersive experience it provides. While our approach made it easier for users to move around and navigate their data in the VR environment, the standard interface still required a significant amount of typing, especially for tasks such as editing and visualizing data. To overcome this issue, we explored the use of hand gestures to manipulate data in VR directly, making data analysis easier and reducing the need for extensive typing or programming skills. Building on this success, we developed a system called ICoN, which combines computational notebooks, gesture-based data manipulation, and visualization in a single workspace within VR. Through a series of tests comparing desktop setups to VR and different workspace configurations, we found that ICoN improved navigation and made data transformation and visualization more intuitive. However, despite the potential of ICoN, the best ways to organize tasks in a virtual environment remain unclear. We then explored how users arrange and interact with data in VR. Participants preferred to organize their work in curved layouts and used non-traditional methods more often than in regular desktop setups. This suggests that virtual environments provide new and more flexible approaches to managing data science tasks. Yet, there are challenges to address, such as scaling up the system to handle larger datasets. Furthermore, manually organizing large notebooks for different tasks can be tiring. To help users manage complex analyses more easily, we developed an organizational guidance system that assists in arranging content with precise spacing and alignment. In our user study, this feature significantly simplified the process of organizing large-scale analyses within immersive environments. Specifically, participants were able to start analyzing data more quickly by reorganizing their workspace with minimal effort. However, to focus the study on organization rather than programming skills, we highlighted certain code blocks to indicate the structural patterns, helping users

concentrate on the layout rather than understanding every line of code. However, in real-world analysis, users still need to understand the logic behind how code runs. That means moving around and exploring large immersive spaces is still a necessary part of working with big analyses. We expect visual tools similar to magnifying glasses that help people focus on small or detailed information to be applied to our system. We also expect to show different levels of information depending on how close or far the person is from the content.

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# Contents

**List of Figures** xiv

**List of Tables** xxi

**1 Introduction** 1

1.1 Motivation . . . 1

1.2 ICoN: Immersive Computational Notebook . . . 5

1.2.1 Features . . . 5

1.3 Research Questions . . . 8

1.4 Structures of this paper . . . 10

**2 Related Work** 12

2.1 Computational Notebook . . . 12

2.2 Iterative Data Analysis Process . . . 13

2.3 Immersive Analytics . . . 13

2.4 Organization Strategies in Immersive Environment . . . 14

2.5 System-level Supports in Organizations . . . 14

**3 Initial Exploration of Immersive Computational Notebooks** 16

3.1 Introduction . . . 16

3.2 Adapting Computational Notebooks to VR . . . 18

3.2.1 Design Goals . . . 18

3.2.2 Adaptations . . . 20

3.3 User Study and Evaluation . . . 24
3.3.1 Study Conditions . . . 24
3.3.2 Task and Data . . . 25
3.3.3 Experimental Setup . . . 28
3.3.4 Participants . . . 28
3.3.5 Design and Procedures . . . 29
3.3.6 Hypotheses . . . 30
3.3.7 Measures . . . 31
3.4 Results . . . 31
3.4.1 Quantitative Results . . . 31
3.4.2 Layout Strategies . . . 35
3.4.3 Qualitative Feedback . . . 36
3.5 Findings and Discussions . . . 38
3.5.1 Is **VR** beneficial? . . . 39
3.5.2 Is "branch & merge" beneficial? . . . 40
3.6 Conclusion . . . 42

**4 Embodied Data Transformation** **43**
4.1 Introduction . . . 43
4.2 Embedded and Embodied Gesture Design . . . 45
4.2.1 Selecting Data Transformation Operations . . . 46
4.2.2 Designing Gestures . . . 46
4.3 User Study . . . 51
4.3.1 Study Conditions . . . 51
4.3.2 Participants . . . 53

4.3.3 Experimental Setup . . . 53
4.3.4 Task and Data . . . 54
4.3.5 Design and Procedures . . . 55
4.3.6 Measures . . . 56
4.3.7 Hypotheses . . . 57
4.4 Results . . . 58
4.4.1 Quantitative Results . . . 58
4.4.2 Layout Strategies . . . 62
4.4.3 Qualitative Feedback . . . 63
4.5 Key Findings and Discussions . . . 66
4.6 Conclusion . . . 70

**5 ICoN: Immersive Computational Notebook for Data Science 71**
5.1 Introduction . . . 71
5.2 Design Rationale and Considerations . . . 74
5.3 ICoN for data science . . . 76
5.3.1 Embodied data science workflow . . . 76
5.3.2 Seamless transitioning . . . 78
5.3.3 Embodied Low-code programming . . . 80
5.4 First user study: Usability . . . 81
5.4.1 Task and Data . . . 82
5.4.2 Experimental Setup . . . 83
5.4.3 Procedure . . . 84
5.4.4 Results . . . 85
5.5 Redesign . . . 85

5.6 Second User Study: Evaluation . . . 86
5.6.1 Study Conditions . . . 87
5.6.2 Data and Task . . . 88
5.6.3 Participants and Apparatus . . . 90
5.6.4 Procedure . . . 91
5.6.5 Hypothesis . . . 92
5.6.6 Measures . . . 93
5.6.7 Results . . . 93
5.7 Key Findings, Observations, and Discussions . . . 98
5.7.1 Usability Study . . . 98
5.7.2 Evaluation Study . . . 102
5.8 Conclusion . . . 104

**6 Exploring Organizational Strategies in ICoN** **106**
6.1 Introduction . . . 106
6.2 User Study and Evaluation . . . 108
6.2.1 Research Questions & Goals . . . 108
6.2.2 Experimental Setup . . . 109
6.2.3 Data . . . 110
6.2.4 Participants . . . 111
6.2.5 Procedure . . . 111
6.2.6 Measures . . . 112
6.3 Results & Discussions . . . 113
6.4 Conclusion . . . 117

**7 Embodied Content Organization for ICoN** **119**

7.1 Introduction . . . 119

7.2 Design Rationale . . . 122

7.2.1 Design Goal . . . 123

7.2.2 Design Framework . . . 124

7.3 Embodied Compositional Structuring for Immersive Computational Notebooks 125

7.3.1 Structures . . . 126

7.3.2 Triggering mechanism . . . 127

7.3.3 Additional interaction with the structures . . . 130

7.4 User Study . . . 131

7.4.1 Study Conditions and Data . . . 132

7.4.2 Task . . . 132

7.4.3 Participants and Apparatus . . . 133

7.4.4 Procedure . . . 134

7.4.5 Measures . . . 134

7.5 Results . . . 134

7.5.1 Quantitative Results . . . 135

7.5.2 Qualitative Feedback. . . . 137

7.6 Discussions . . . 138

7.7 Conclusion . . . 143

**8 Conclusions & Future Works** **144**

8.1 Conclusions . . . 144

8.2 Limitations and Future Works . . . 147

8.2.1 Broader applicapability . . . 147

8.2.2 Optimizing interaction for decision-making process . . . 147
8.2.3 Optimizing interaction in selecting objects . . . 148
8.2.4 Learning curve in gestural interaction . . . 149
8.2.5 Integrating LLM to support evolving analysis . . . 150
8.2.6 Transition between Desktop and VR . . . 150
8.2.7 Scalability in embodied data transformation . . . 151
8.2.8 Collaborations . . . 152

**Bibliography** **153**

**Appendices** **170**

**Appendix A Initial Explorations of Immerisve Computational Notebooks** **171**
A.1 Informed Consent Form . . . 172
A.2 Pre-Study Questionnaire . . . 173
A.3 Post-Study Questionnaire . . . 180
A.4 IRB Approval Letter . . . 186

**Appendix B Embodied Data Transformation** **188**
B.1 Informed Consent Form . . . 189
B.2 Pre-Study Questionnaire . . . 190
B.3 Post-Study Questionnaire . . . 193
B.4 IRB Approval Letter . . . 200

**Appendix C ICoN: Immersive Computational Notebook for Data Science** **202**
C.1 Informed Consent Form: First User Study . . . 203
C.2 Post-Study Questionnaire: First Study . . . 204

C.3 Informed Consent Form: Second User Study . . . . . 210
C.4 Post-Study Questionnaire: Second Study . . . . . 211
C.5 IRB Approval Letter . . . . . 217

**Appendix D Exploring Organizational Strategies in ICoN** **219**

D.1 Informed Consent Form . . . . . 220
D.2 Post-Study Questionnaire . . . . . 221

**Appendix E Embodied Organizational Guidance for ICoN** **227**

E.1 Informed Consent Form . . . . . 228
E.2 Post-Study Questionnaire . . . . . 229

# List of Figures

1.1 Illustration of WIMP interfaces in (a) Embodied Data transformation, and (b) Initial Exploration of ICoN. . . . . 2

1.2 Illustration of branching techniques in the context of immersive computational notebooks. . . . . 3

1.3 Illustration of Embodied Data transformation. . . . . 4

1.4 Illustration of seamless transition between embodied data transformations, and visualizations in the context of immersive computational notebooks. . . 6

1.5 Illustration of the triggering mechanism to transform target cells into the provided structures. . . . . 7

3.1 A demonstration of the immersive computational notebook system featuring the branching capabilities. The user can work with windows containing multiple cells, which are interconnected to indicate execution order. (a) and (b) shows branches created at different locations of the notebook for testing multi-level hypotheses. (c) subsequently merge these branches for streamlined result comparisons, with six results—three branches at (a) × two branches at (b)—presented in the output of the window. . . . . 17

3.2 Visual representation (top) of the Branch&Merge mechanism within computational notebooks, as instantiated in a VR (bottom). Different hues within the results are employed to illustrate the independent storage of variables across branches. The figure is segmented into five key operations: (a) regular notebooks, (b) initial creation of the branch, (c) merge back to a singular code execution path, (d) initiation of the second branch, and (e) final merging process to facilitate value comparisons across all initiated branches. . . . . 19

3.3 Illustrations of gestures interactions in the **VR** environment. . . . . 21

3.4 Demonstrations of conditions tested in our study. User scrolling to navigate in Desktop (top), and walking and rotating their body to navigate in VR (bottom). In addition, the user used a physical keyboard to write codes in Desktop, while used a virtual keyboard in VR. . . . . 26

3.5 Completion time for VR and Desktop in the navigation task. (a) the time spent for completing deletion, and (b) the time spent completing relocation. Solid lines indicate statistical significance with $p < 0.05$. The tables below show the Cohen's D effect sizes for significant comparisons. Circles with black borders indicate the condition with better results. . . . . 32

3.6 Analysis of four testing conditions in the comparison task. (a) the time spent completing the task, (b) the number of executions performed, (c) the time spent for text input, (d) the time spent completing the task excluding the text input interaction time, (e) the total time spent for creating all branches in Desktop and VR, (f) the average time spent for creating a branch in Desktop and VR. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $0.05 < p < 0.1$. The tables below show the Cohen's D effect sizes for significant comparisons. Circles with black borders indicate the condition with better results. . . . . 33

3.7 User ranking of overall user experience. Solid lines indicate significant differences with $p < 0.05$. The tables on the right show the Cohen's D effect sizes for significant comparisons. Circles with black borders indicate the condition with better results. . . . . 35

3.8 Subjective ratings on (a) physical demand, (b) mental demand, (c) engagement, and (d) effectiveness by task. Towards the right end of subfigures means better-perceived results. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $0.05 < p < 0.1$. . . . . 37

3.9 Two layout strategies used by our participants in Desktop+Branch(Left) and in VR+Branch(Right). . . . . 38

3.10 Navigation distance of different navigation methods across Desktop and VR: (a) the number of scroll ticks on the Desktop, (b) the degree of head rotation, and (c) the distance traversed in VR. Solid lines indicate statistical significance with $p < 0.05$. The tables below show the effect sizes for pairwise comparison. Circles with black borders indicate less navigation distance required. . . . . 41

4.1 Four conditions designed for performing data transformation in the user study, including a combination of desktop or VR environments, and WIMP or gesture interactions. . . . . 44

4.2 VR data table and gestures for data transformation tasks in the VR+Gesture condition. VR controllers, represented as hand models in the VR prototype and in the figure above, are used to perform these operations. The operation that was excluded from the study is marked with *. . . . . 48

4.3 Desktop data table and gestures for data transformation tasks in the Desktop+Gesture condition. The operation that was excluded from the study is marked with *. . . . . 49

4.4 Our study compares two primary factors, leading to four conditions. . . . . 53

4.5 Measurement of time, the total number of operations, recall score, the number of delete operations, and the number of tables left by task. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below show the effect sizes for pairwise comparison. Circles with black borders indicate the winning conditions. . . . . 59

4.6 Subjective ratings on mental demand, physical demand, learnability, engagement, and usability by task. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. . . . . 61

4.7 User ranking of overall user experience for each condition. Solid lines indicate significant differences with $p < 0.05$. . . . . 62

4.8 Four layout strategies used by our participants on Desktop. . . . . 64

4.9 Three layout strategies used by our participants in VR. The red dot indicates the position of the participant. . . . . 65

5.1 User performs data science tasks with an immersive computational notebook (ICoN). They can seamlessly transition between notebooks and embodied workspaces within a unified environment. Specifically, (a-1) a user can directly pull out a data table from the notebook, and create visualizations from the data table through embodied interactions. (a-2) A user can also pull out visualizations that are embedded in the notebook and manipulate them, for example, by grabbing an additional data dimension from the table and adding it to a 2D scatter plot as a new axis (left) to create a 3D scatter plot (right). After exploring data tables and visualizations, the user can put them back into the computational notebook to update the code. . . . . 72

5.2 Illustration of iterative data science workflow in ICoN. . . . . 77

5.3 Gesture interactions to transit between computational notebooks, data transformation, and data visualizations. . . . . 78

5.4 Putting transformed data table into a code cell updates the code in the computational notebook. Users can either (a) create a new variable by putting their work into an empty cell, or (b) update an existing variable by putting their work back into a cell that was previously pulled. . . . . 81

5.5 A instructed scenario in Task 1 to remove outliers. (a) The user identifies an outlier within a visualization cell that needs to be eliminated from the data cell. (b) To delete the outliers, the user can navigate to the data cell to pull out the data table. (c) Identifying an outlier directly within the data table can be challenging, necessitating the creation of a visualization to pinpoint the outlier. The user can then remove the outlier directly from the visualization, subsequently updating the data table with these changes. (d) Next, they can further explore the data table and put it back into the computational notebook. (e) Finally, the user confirms that the outlier has been successfully removed from the computational notebook. . . . . 82

5.6 Our study focused on two primary comparison factors, leading to four testing conditions. . . . . 87

5.7 Illustration of tested conditions in our study. In the Desktop (top), users navigate by scrolling, while in the VR (bottom), they navigate by walking and rotating their heads. Additionally, the computational notebook and embedded/embodied workspace are spatially disconnected in the Separated (left), whereas in the Unified, they are spatially connected (right). . . . . 89

5.8 Completion time and transition count across conditions: (a) and (b) indicate the time taken to complete each task. (c) shows the total number of transitions, while (d) shows the interactive transitions, and (e) shows the navigational transitions count. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below display effect sizes for pairwise comparisons, with black-bordered squares highlighting the outperforming conditions. . . . . 94

5.9 Measurements of (a) number of relocating computational notebooks and data artifacts, (b) number of deletion operations performed, and (c) amount of content left in the given environment. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below show effect sizes for pairwise comparisons, with black-bordered squares highlighting the outperforming conditions. . . . . 96

5.10 Participants' responses: (a) mental demand, (b) physical demand, (c) engagement, and (d) overall user experience ranking. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below display effect sizes for pairwise comparisons, with bold text highlighting the outperforming conditions. . . . . 97

5.11 A bird's eye view of the layout strategy in ICoN. Participants manage their workspace in a layered hierarchy. (a.1) participants pull out a data table and position it at a closer depth, (a.2) while the visualizations derived from that data table are placed at the same depth. (a.3-4) repeated processes with other visualizations. (b) This results in the creation of a hierarchically structured workflow. . . . . 100

6.1 Cells are displayed linearly on a desktop computational notebook, resulting in a linear execution order (left). Users then wonder about the organizational strategies for using computational notebooks in an immersive environment (right). . . . . 107

6.2 Illustration of the experimental setup. (a) Cells are stacked in random order. (b) A closer look at the design of the cell, where codes and outputs are located at the center. Four holes on the side are available for visualizing the execution order. . . . . 109

6.3 Implemented spatial arrangements. (a) Participants were fully surrounded by code cells, forming a complete cylindrical layout, whereas (b) Cells were arranged in a half-cylindrical layout, providing free space behind the participants. (c) Cells were set up only in front of the participants but still in a curved formation, forming a quarter of a cylindrical layout. (d) Cells were placed in a flat wall shape only found in the Simple. . . . . 113

6.4 Illustration of execution order (top) and clarification of corresponding order (bottom). (a) Cells followed linear execution order. (b) Cells formed multiple rows, whereas (c) cells were set up in multiple columns. (d) Cells initially followed a linear order but switched to a branching strategy to facilitate code comparison. (e) Cells involved multiple execution orders simultaneously; for instance, Multi-Row, Column, and Branch were used together. . . . . 116

6.5 Illustration of space management strategies within ICoN. (a) participants organized the cells in a structured manner, whereas in (b), the placement of cells appeared less organized. . . . . 118

7.1 Cells are displayed linearly on a desktop computational notebook, resulting in a linear execution order (left). Users then wonder about the organization's strategies for using computational notebooks in an immersive environment (right). . . . . 120

7.2 The type proxies used to organize the immersive computational notebooks. . 122

7.3 Design framework for embodied compositional structuring. . . . . 124

7.4 Composition of structures for embodied compositional structuring based on our design framework. . . . . 126

7.5 Illustrations of gesture-based interactions used to trigger provided structures and interact with the embodied compositional structuring. . . . . 129

7.6 Participants' completion time and moved distance across conditions. Solid lines indicate statistical significance with $p < 0.05$, and the tables show effect sizes for pairwise comparisons, with bold text highlighting the outperforming conditions. . . . . 135

7.7 Participants' subjective ratings: (a) physical demand, (b) mental demand, (c) difficulty level, (d) learn a lot, and (e) preference. Solid lines indicate statistical significance with $p < 0.01$, and dashed lines indicate statistical significance with $p < 0.05$. Additionally, the tables display effect sizes for pairwise comparisons, with bold text highlighting the conditions that outperform others. . . . . 136

7.8 Illustrations of comparisons between Manual and Compositional. (a) Participants moved significantly less in the Compositional, as indicated by fewer blue dots. In execution-focused workspaces, (b) Compositional enabled the construction of well-organized structures with clearly positioned execution indicators. (c) Participants in Compositional built more continuous workflows, in contrast to the fragmented workflows observed in the Manual. (d) In narrative-focused workspaces, participants in Compositional actively piled or folded lower-priority cells and hid the execution indicators, while those in Manual largely left their previously built execution-focused structures. . . . 139

7.9 Illustrations of unique strategies and behaviors during the organization process. (a) A participant (P5) in the Manual created multiple sections from a central point, forming a flower-like shape, with each "petal" representing a sub-task in the analysis. (b) While participants were building Skip-Layer, they moved back and forth, as the content was not clearly visible from a distance. . . . . 142

# List of Tables

4.1 A summary of our supported data transformation operations and their matching gestures. . . . . 47

6.1 Distribution by spatial structures in ICoN. . . . . 115

6.2 Distribution of execution order in ICoN. . . . . 116

# Chapter 1

# Introduction

## 1.1 Motivation

Computational notebooks provide a unified interface that integrates code, documentation, visualizations, and data, allowing analysts to perform iterative tasks seamlessly [1]. With the growing complexity of data analysis, traditional WIMP (windows, icons, menus, pointers) interfaces (see Fig. 1.1)become increasingly limited when dealing with more advanced and non-linear workflows required in modern data science [2]. For instance, tasks such as data transformation and visual exploration often require not only extensive text input but also extensive navigation across multiple views, making the traditional desktop interface ineffective.

Motivated by these challenges, we sought to explore the potential of immersive technologies in addressing the limitations of the WIMP interface. Immersive technologies, such as virtual reality (VR), offer new possibilities for interaction by leveraging embodiment, where users engage with data through physical gestures and direct manipulation [3, 4]. These technologies create a more intuitive environment for analysts to interact with data, as the immersive space offers richer sensory information, improved depth perception, and better spatial awareness. We hypothesized that bringing computational notebooks into immersive environments could enhance analysts' ability to navigate complex datasets, explore data transformations, and manage large-scale visualizations more efficiently.

Our first step in this exploration was to adapt the computational notebook into an immersive environment. We aimed to preserve the notebook's strengths, such as the integration of code and visualizations, while enhancing its usability through embodied interactions. We found that participants were able to move beyond linear workflows, which often fail to capture the complexity of analytical processes. They instead build non-linear structures with greater organizational freedom, enabled by embodied interactions. However, initial




(a) Embodied Data Transformation (b) Initial exploration of ICoN

Figure 1.1: Illustration of WIMP interfaces in (a) Embodied Data transformation, and (b) Initial Exploration of ICoN.

attempts revealed a key limitation: the standard interface of computational notebooks in immersive environments still required extensive text input, particularly for tasks such as data transformation and visualization.

To address these limitations, we introduced the concept of embodied data transformation. This approach replaced traditional coding-based operations with gesture-based, direct data manipulation, allowing analysts to transform and explore data using their physical movements rather than writing code. By enabling analysts to interact with data in a more intuitive manner, we found that this reduced the cognitive load compared to traditional interfaces. Furthermore, we envision that analysts with less programming knowledge could engage in complex data analysis tasks more effectively, making the entire process more accessible and efficient.

Building on the success of this initial exploration, we developed ICoN (Immersive Computational Notebook), a system designed to integrate computational notebooks with embodied data transformation and visualization within a unified workspace. ICoN enables analysts to perform comprehensive data science tasks—from data manipulation to visualization—through embodied interactions, facilitating seamless transitions between various data science workflows. We found that the unified workspace in ICoN offers the advantage of combining immersive interaction with the rigor of traditional computational notebooks, providing a hybrid environment that enhances navigation and comparison across datasets. However, while ICoN demonstrated substantial potential in enhancing data science performance, specific organizational strategies, such as managing execution orders and workspaces in immersive



Figure 1.2: Illustration of branching techniques in the context of immersive computational notebooks.

environments, remained underexplored.

In our next phase of research, we aimed to address this gap by examining how analysts spatially arrange and interact with computational notebooks in immersive environments. Through a user study, we found that participants favored organizing their work in half-cylindrical layouts and engaged more frequently in non-linear analysis compared to traditional desktop setups. This suggests that immersive environments encourage analysts to engage with their data in more flexible and dynamic ways that better align with their perceived analytical reasoning processes. However, we observed that participants were hesitant to move frequently and organize documents as the number of code cells increased, despite recognizing the importance of organization for a comprehensive understanding of the code.

We believe this hesitation highlights the need for tools that assist users in organizing documents efficiently, especially as the complexity and number of code increase. To address this, our work introduces an organizational guidance system that helps analysts structure code in a more organized, clearly conveying execution logics, alignment, spacing, and ordering. Findings from our user study indicate that participants were able to construct well-organized structures more quickly and with significantly less physical effort when using the guidance system. However, we also observed that participants tended to rely heavily on the guidance, which potentially reduced their engagement with complex reasoning processes and led

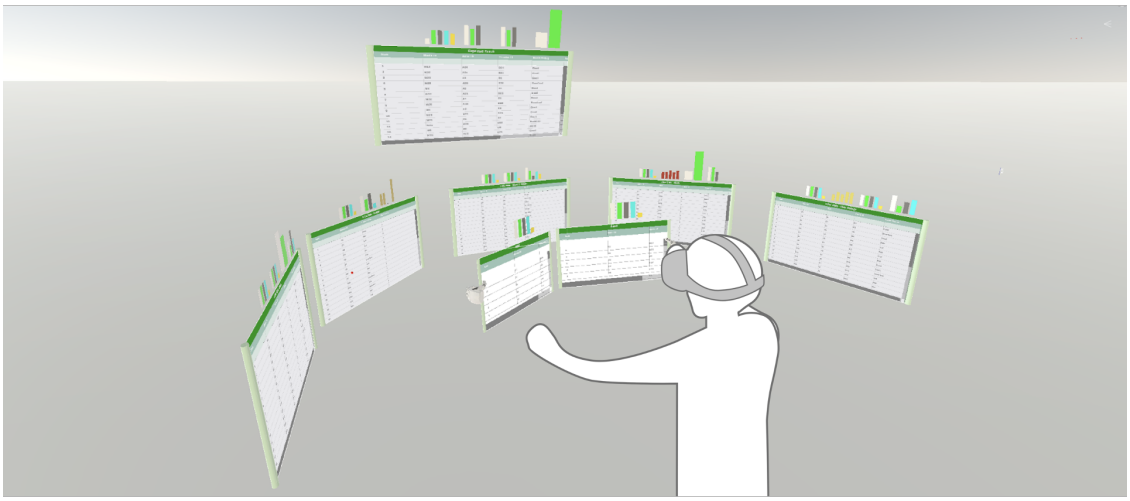


Figure 1.3: Illustration of Embodied Data transformation.

to oversimplified structures. Additionally, while many participants actively used depth to emphasize key findings, the current interaction design for triggering depth-based structures lacked support for inspecting content placed at a distance, requiring users to move closer to view the details.

Taken together, by supporting analysts in building well-organized structures—with clearly defined execution logic, spacing, and alignment—our system helped mitigate the physical and cognitive demands that often arise in large-scale immersive workspaces. However, our work also revealed several limitations and uncovered important directions for future research. Notably, as immersive notebooks grow in complexity and scale, analysts face increasing challenges in inspecting content from a distance to organize the artifacts in immersive computational notebooks. A promising direction is the integration of visualization techniques such as lenses and summarization proxies, which could support near-far interaction by presenting contextual overviews or abstracted content when users are positioned farther away. These methods may help analysts maintain awareness and reduce physical navigation, especially in workspaces where content is widely distributed or deeply layered in 3D space.

In addition to distant inspection, future systems could also address the difficulty of transitioning between immersive and traditional desktop environments. While immersive spaces offer spatial flexibility and embodied interaction, computationally intensive tasks like data loading and editing large code blocks may still be more practical on desktop systems. Seamless transitions between platforms without disrupting spatial orientation or execution logic

will be essential for supporting hybrid workflows. Furthermore, the potential for collaborative analysis in immersive settings remains unexplored, raising important questions about how users can co-construct, share, and reason about computational workflows in shared 3D spaces. Addressing these challenges will be critical for advancing immersive notebooks beyond individual use, toward systems that support more scalable, fluid, and collaborative data science workflows.

## 1.2 ICoN: Immersive Computational Notebook

ICoN is a system that enables embodied interaction throughout the entire data science pipeline within a unified workspace integrated into a computational notebook environment. Specifically, ICoN allows analysts to seamlessly transition between different workspaces to perform data science tasks using embodied interaction, as shown in Fig. 5.3. In addition, ICoN leverages the benefits of the nature of immersive environments, such as enhanced depth perception, improved spatial orientation, a large workspace, intuitive interaction, and increased engagement compared to traditional desktop setups [5, 6, 7]. Furthermore, users can physically move and interact within ICoN, engaging in actions such as walking and gestural embodied interaction. The current version of ICoN is built using an immersive Virtual Reality (VR) headset, allowing users to interact with the system through natural, hand-based gestures, primarily using their dominant hand.

### 1.2.1 Features

ICoN focused on gesture-based data science tasks; we aimed to provide features that facilitate this style of analysis. Below, we outline the core set of features supported in ICoN.

**Branch&Merge.** To support analysts in duplicating content for testing multiple hypotheses and intuitively generating comparisons while reviewing all generated results, we implemented Branch&Merge features in the system. Analysts can grab a specific window and split it apart, creating a branch upon releasing it. Once the branches are created, they can be merged into a single window to analyze all results in one place, as illustrated in Fig. 1.2.

**Embodied Data Transformation and Visualizations.** In ICoN, analysts can intuitively explore data through gestural interactions, such as data transformation and visualization.

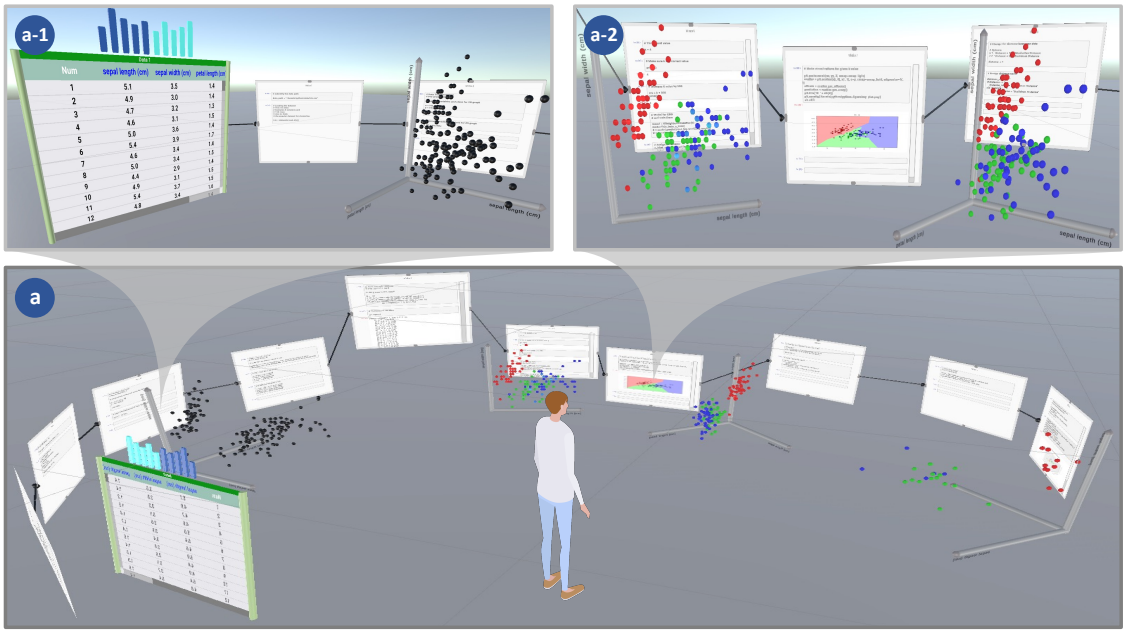



Figure 1.4: Illustration of seamless transition between embodied data transformations, and visualizations in the context of immersive computational notebooks.

This means that even analysts with limited coding knowledge can deeply explore data, uncover hidden patterns, and easily gain insights that may be missed in static images within a traditional computational notebook. We integrated the embodied data transformation approach (see Fig. 1.3) and developed an embodied data visualization system, as existing tools do not fully support bare-hand interaction [5, 8].

**Seamless Transitions.** Frequent transitions are inevitable when performing data science tasks within a workflow. In ICoN, we facilitate these transitions through embodied interactions, such as pull-out and put-in gestures, combined with physical walking. Users can pull out data tables to edit them without writing extensive code and convert static graphs into more interactive visualizations. By employing a low-code mechanism [9], analysts can update their explorations seamlessly without additional coding. To do this, they can put their explored data back into the computational notebook, again, without needing to write further code (see Fig. 1.5).

**Compositional Structuring.** One of the key benefits of using ICoN is its ability to break away from traditional linear layouts by allowing flexible organization of codes that better reflect non-linear analytical reasoning (see Sec. 6.3). However, as the number of cells increases, organizing contents through manual embodied interaction becomes physically de-

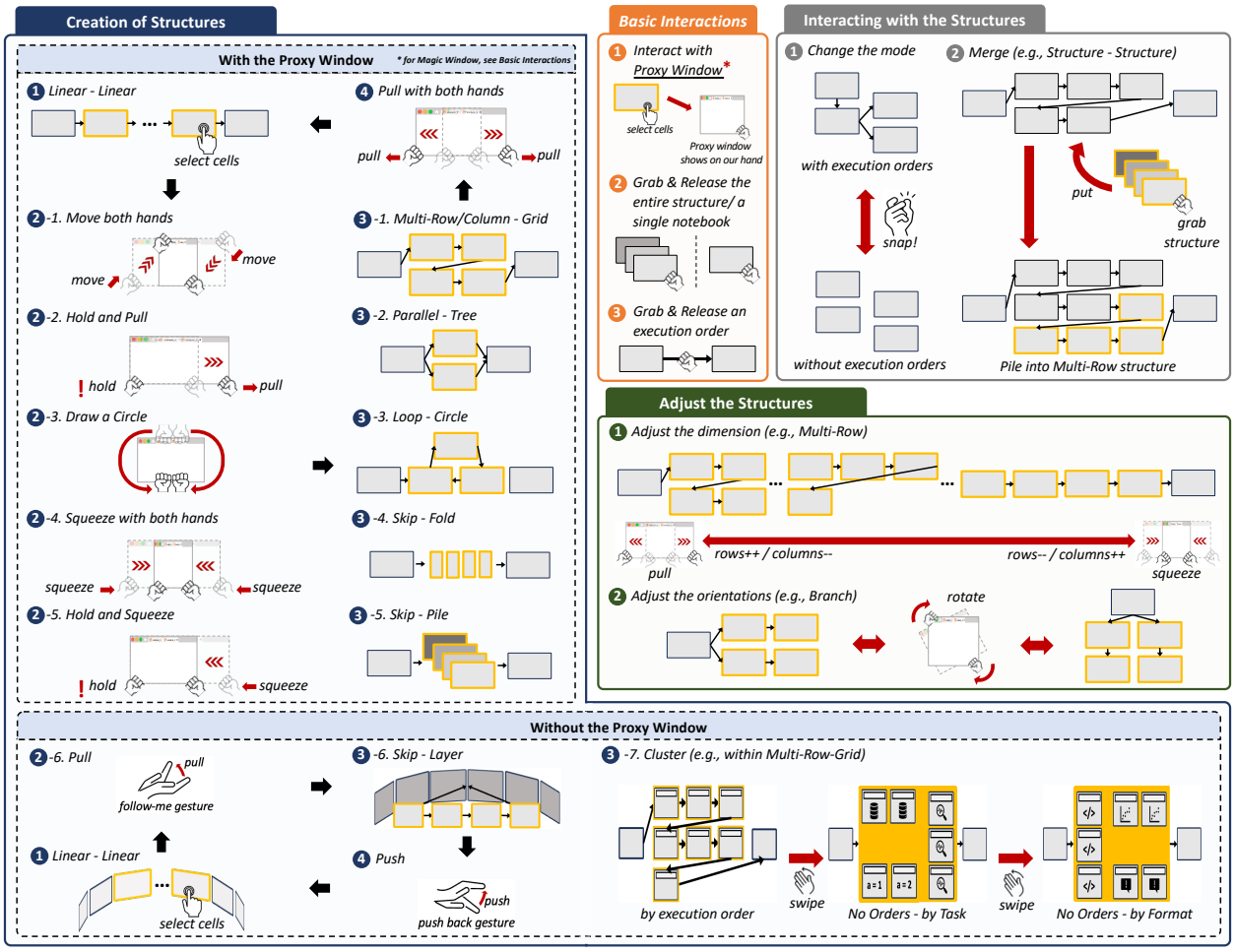



Figure 1.5: Illustration of the triggering mechanism to transform target cells into the provided structures.

manding, requiring analysts to arrange cells one by one. To address this challenge, we introduce embodied compositional structuring, which enables users to rapidly structure execution logic and spatial placement of cells with significantly less effort. For instance, users can select target cells and perform gestural interactions (see Fig. 1.5) to transform them into well-organized structures with clear execution logics, spacing, and alignment. Our system includes ten distinct structures designed to comprehensively support a wide range of use cases in computational notebooks, from exploratory analysis to storytelling.

## 1.3 Research Questions

***RQ1: How can VR's Spatial and Embodied nature enhance navigation and comparison in computational notebooks?***

Previous research on improving computational notebooks has primarily focused on traditional desktop environments. While these studies have provided valuable insights into supporting non-linear data analysis, space constraints remain an issue when performing complex tasks on a limited desktop screen. To address these challenges, we first adapted the computational notebook to immersive environments. Specifically, we introduced an additional hierarchy layer to improve content management, adopted a curved layout for better content organization, and designed gesture-based interactions, including a branch-and-merge gesture to assist with comparison tasks. To systematically evaluate the proposed research question, we conducted a controlled user study comparing computational notebooks on the desktop and in VR, with and without branch-and-merge capabilities.

***RQ2: How does VR help Data Transformation?***

Building on previous explorations of adapting computational notebooks to immersive environments, we recognized that extensive text input in such settings poses significant challenges. We further anticipated that this limitation could extend to the broader use of immersive computational notebooks for performing entire data science tasks, including data transformation and visualization. To address this, we explored the potential benefits of performing data transformation tasks in an immersive environment using embodied gestures instead of extensive coding. To systematically evaluate how VR helps data transformation, we conducted a comparison study in which users performed data transformation tasks across different computing environments (Desktop vs. VR) and interaction mechanisms (WIMP

vs. Gesture).

***RQ3: How can we incorporate embodied workspace in immersive computational notebooks?***

Building on the successful initial exploration of immersive computational notebooks and embodied data transformation, we aim to integrate these approaches into a unified workspace, enabling the completion of entire data science tasks within computational notebook setups in an embodied manner. We decided to call this approach "ICoN", a system that utilizes embodied interaction to create a hybrid paradigm, bridging the computational notebook workspace with the embodied interaction workspace for tasks such as data transformation and visualization. To systematically evaluate the effectiveness of integrating computational notebooks and embodied workspaces, we conducted a comparison study. This study included comparisons of traditional desktop settings using WIMP interactions and a separate workspace where users had to switch entirely between the computational notebook and data science tasks.

***RQ4: What are organizational strategies in the immersive computational notebook?***

While ICoN enables more intuitive and in-depth data exploration within computational notebook setups, we observed that organizational strategies significantly impact the overall analysis performance. Specifically, we found that the cylindrical layout restricts available workspace as the complexity of the workflow increases when creating a depth hierarchy. To better understand spatial structures in ICoN, we aimed to explore how computational notebooks are organized in immersive environments and how execution orders can be visualized. Additionally, we sought to investigate how the larger display space in immersive environments encourages participants to engage in non-linear analysis compared to traditional desktop setups. To systematically explore these goals, we conducted an exploratory user study under two conditions to capture a range of organizational strategies: the "Simple" condition, involving fewer code cells to mimic basic data analysis tasks, and the "Complex" condition, which included more code cells to represent more complex data analysis workflows.

***RQ5: How can large-scale analysis be effectively organized within immersive computational notebooks?***

While immersive computational notebooks offer greater flexibility to shape the workspace freely, manually organizing a large number of cells through embodied interaction becomes

increasingly effort-intensive, especially when maintaining both execution logic and visual coherence. To reduce this effort, we introduce an embodied compositional structuring that leverages system-level supports in organizations, enabling users to construct well-organized structures in immersive environments rapidly. Our provided structures encapsulate common analytical workflows through combinations of execution order, orientation, and layout, supporting both analysis and presentation tasks. We conducted a controlled user study comparing manual and embodied compositional structuring in immersive environments.

## 1.4 Structures of this paper

Chapter. 1 introduces the background, motivation, and overarching research questions guiding this work.

Chapter. 2 presents a literature review on the foundational theories of computational notebooks, existing iterative data analysis processes, immersive analytics, and organizational strategies within immersive environments.

Chapter. 4 addresses Research Question 1 by presenting user studies that explore how the integration of computational notebooks into immersive environments improves navigation and comparison analysis.

Chapter. 3 addresses Research Question 2 by presenting a user study that evaluates how gesture-based data transformation in immersive environments enhances performance compared to traditional WIMP interfaces.

Chapter. 5 addresses Research Question 3 by prototyping and implementing a data science platform that enables users to perform complete data science tasks, such as data transformation and visualization, within computational notebooks in an embodied manner. Two user studies are presented to assess the usability and effectiveness of these features compared to traditional WIMP interfaces on desktop setups.

Chapter. 6 addresses Research Question 4 by presenting a user study that investigates how execution order impacts organizational strategies and how large display spaces encourage analysts to engage more in non-linear analysis.

Chapter. 7 addresses Research Question 5 by presenting a user study that investigates the effectiveness of embodied compositional structuring in managing large-scale immersive com-

putational notebooks.

Finally, Chapter. 8 concludes by summarizing the proposed research questions, discussing general limitations, and offering directions for future research.

# Chapter 2

# Related Work

## 2.1 Computational Notebook

The concept of the computational notebook first emerged from Knuth's study of literate programming, aiming to create a computational narrative that seamlessly integrates visuals, text, and analytical insights within a single document [1, 10, 11]. This approach has led to the widespread adoption of computational notebooks in data science, as they enable a comprehensive analysis process. Numerous applications have been introduced, notably Jupyter Notebook [12], a leading computational notebook application [13], which operates on a linear execution order. Following this, alternative approaches have been explored, such as the non-linear representation in Observable [14] and Apache Zeppelin [15], focusing on managing big data. Despite these explorations, computational notebooks still introduce several challenges. Chattopadhyay et al. interviewed 156 data scientists to shed light on current issues related to the use of computational notebooks [2].

In et al. introduced the concept of using computational notebooks in immersive spaces, where users can intuitively navigate through notebooks in a larger space [16]. They organize cells and outputs in separate windows, which are interconnected to form a complete notebook. They evaluated representative data science tasks, such as hyperparameter tuning, which require extensive navigation and comparison to find optimal parameter values. While immersive computational notebooks significantly improve navigation performance, text input interaction remains a challenge for immersive devices. Additionally, the limited interaction in transforming and visualizing data in traditional notebooks continues to pose challenges in this approach.

## 2.2 Iterative Data Analysis Process

In data science, analysts often transition between various tasks or stages within the iterative data analysis workflow [9], such as moving from data transformation to data visualization. These transitions are crucial for maintaining workflow continuity, which is critical for the practical analysis and interpretation of complex datasets. However, a significant challenge in facilitating these transitions is that analysts often rely on multiple tools and environments for different tasks, making transitions complex. Moreover, building on successful explorations from immersive analytics [3, 4, 17], frequent switching between different types of devices—such as moving from a non-immersive to an immersive environment [18, 19, 20]—can introduce an additional layer of complexities [21]. For instance, analysts may need to use immersive visualization tools to deeply explore and interact with the data, but then transition to a desktop to perform more computationally intensive tasks. Furthermore, the need to manage and integrate data across different platforms and formats, which can easily introduce errors, inconsistencies, and inefficiencies [10, 22]. These challenges underscore the need for integrated data science tools that operate within a unified computing environment.

## 2.3 Immersive Analytics

Immersive analytics leverages engaging and interactive technologies like VR and AR to significantly enhance data analysis by providing users with a more intuitive, embodied experience [3, 4, 17]. By enabling users to explore and interact with data in a physical space, immersive analytics enhances comprehension, encourages deeper insights, and facilitates a more intuitive understanding of complex datasets [5, 8, 23]. While tools like ImAxes offer a fully immersive visualization authoring experience, many existing solutions still require users to design and configure visualizations on a desktop before viewing them in an immersive setup, limiting the potential for real-time interaction and adaptation. Beyond visualizations, data transformation tools have been introduced for a broader audience by utilizing graphical user interfaces (GUI) [24, 25, 26] or using gestures [27, 28, 29]. Notably, In et al. introduced immersive data transformation, enabling users to perform data cleaning and transformation within a fully embodied workspace, incorporating more visualizations and embodied gestures [30]. They found that embodied workspace facilitates more intuitive explorations; however, analysts found it challenging to track their workflow in environments that primarily

focus on data artifacts without structured guidance.

## 2.4 Organization Strategies in Immersive Environment

In Immersive Analytics [4], previous research has highlighted that space management [31, 32] and content organization [33, 34] are pivotal in the data analysis process. Specifically, Liu et al. discovered that a half-cylindrical shape is the most preferred layout for multiple small data visualization blocks [33]. In contrast, Satriadi et al. observed that a quarter-cylindrical layout was predominantly used for managing hierarchical multi-view geospatial data [34]. Building on these findings, Luo et al. investigated how physical surroundings and co-located collaboration impact the spatial organization of virtual content in augmented reality (AR) [35]. They identified nine distinct layouts that varied based on the physical environment, spatial structuring, and workflow dynamics. However, these investigations mostly focused on standard digital content where sequence does not critically affect workflow. Few studies have explored sequenced workflows in immersive environments [16, 36], often adopting a half-cylindrical layout as their initial setup due to its efficiency in content management [33]. However, this perspective generally overlooks a detailed analysis of the organizational strategies that might be critical in a sequenced workflow.

## 2.5 System-level Supports in Organizations

System-level support in organizations aims to support users in structuring workflows by utilizing the composition of pre-defined structures [37, 38]. Early work focused on rule-based layouts and heuristic alignment aids, which helped maintain clarity and consistency, particularly in domains such as design tools and collaborative whiteboards [39, 40, 41]. For instance, Figma [42] enables designers to quickly initiate projects using predefined templates that provide structured starting points, while Miro [43] supports workflow visualization by offering templates with consistent spacing, grouping, and alignment. In the context of computational notebooks, most existing mechanisms are designed to support the progression of analysis, such as creating new branches [44], but they rarely facilitate the reorganization of existing content into desired structures. While some systems have introduced features to reorganize notebook layouts, their focus is often on transforming notebooks into dashboards,

narratives, or visual documents [45]. Moreover, when notebooks are extended into immersive environments, an additional dimension—depth—becomes a meaningful organizational axis. However, system-level support in organizations that consider execution orders within immersive environments has been underexplored. To address these gaps, we explore system-level support to facilitate the organizational process in a way that accounts for both execution order and spatial depth.

# Chapter 3

# Initial Exploration of Immersive Computational Notebooks

## 3.1 Introduction

The computational notebook has gained substantial popularity across diverse domains due to its versatility, characterized by its seamless integration of code, documentation, and visual outputs in a unified interface, ease of sharing and replication, and interactive features with real-time feedback. Data analysts leverage these capabilities for tasks ranging from constructing analytical pipelines to debugging and comparative analysis [2].

However, as data analysis grows in complexity, the standard computational notebook's user interface shows limitations in supporting the aforementioned tasks. Specifically, *navigating* through extensive notebooks becomes increasingly challenging, complicating tasks like identifying issues in the analytical pipeline or refactoring code [22]. Analysts often have to scroll up and down through lengthy sections multiple times, relying heavily on their working memory for off-screen content, leading to high context-switching costs [46]. Additionally, modern data analysis often involves *comparisons*, such as determining optimal parameters for analytical models. Common practices, like duplicating code or notebook, complicate code and execution management by introducing non-linearities [47]. While literature identifies other challenges with computational notebooks [2], this project focuses on enhancing *navigation* and *comparison*, which are primitive components of data analysts' workflows [48].

Efforts to improve navigation and comparison in computational notebooks within the desktop environment exist [44]. However, the inherent limitations of desktop display and interaction paradigms restrict the spatial presentation and interaction modes with computational notebooks. Thus, we explore opportunities offered by emerging technologies, specifically virtual reality (VR). VR headsets allow interaction with 2D and 3D graphics and interfaces in an




Figure 3.1: A demonstration of the immersive computational notebook system featuring the branching capabilities. The user can work with windows containing multiple cells, which are interconnected to indicate execution order. (a) and (b) shows branches created at different locations of the notebook for testing multi-level hypotheses. (c) subsequently merge these branches for streamlined result comparisons, with six results—three branches at (a) × two branches at (b)—presented in the output of the window.

expansive space, introducing new human-computer interaction possibilities for non-linear notebooks. Preliminary research in using VR for data science shows promising benefits. For example, VR allows analysts to use its large space as an external memory layer with spatial semantic meanings to better support information retrieval [49, 50, 51]. Physical interactions in VR, including natural walking and embodied gestures, provide rapid information access and command execution [6, 30, 52, 53]. Consequently, our overarching research question is: **Can VR's spatial and embodied nature enhance navigation and comparison in computational notebooks?**

To approach the proposed research question, we first adapted the computational notebook for the VR environment. Specifically, we introduced an additional hierarchy layer to facilitate notebook content management, adopted a curved layout for content placement, and designed gesture-based interactions, including a branch&merge gesture to assist comparison. To systematically verify and understand the potential benefits of virtual reality, we conducted a controlled user study to compare computational notebooks on the desktop and in VR, both with and without branch&merge capability. The study task comprised two phases: first, participants were asked to *navigate* through a presented computational notebook, identifying

and rectifying deliberate issues; second, they were required to determine optimal parameter values through *comparisons*. Pre-configured codes were provided to reduce the need for constructing a notebook from scratch, enabling participants to focus on *navigation* and *comparison* tasks. We noticed that participants encountered significant challenges in editing text while in VR. After excluding the text editing time from all conditions, we found that VR had better navigation performance than the desktop, and the branch&merge functionality significantly facilitated the comparison process. The contributions of this work are twofold: 1) the adaptation of computational notebooks from desktop to VR, and 2) empirical knowledge about using computational notebooks in VR.

## 3.2 Adapting Computational Notebooks to VR

Our primary objective is to examine the user experience of computational notebooks in VR and to explore the potential advantages VR may offer. A crucial initial step is adapting the computational notebook system for VR use. While the desktop version of the computational notebook is well-established, transitioning it to a VR setting introduces unique challenges. These include determining how to visually represent and spatially position the notebook in the VR space and identifying necessary interactions to facilitate its use in this immersive environment. As a preliminary step for designing VR-compatible computational notebooks, we aimed for a smooth transition for analysts by maintaining design consistency with familiar desktop counterparts, while also leveraging VR's distinctive capabilities where beneficial. This section details our design objectives, centered on enhancing the *navigation* and *comparison* functionalities of computational notebooks, and discusses our primary design considerations and decisions.

### 3.2.1 Design Goals

**Navigating** a computational notebook involves an analyst shifting their focus to a different section of the notebook by actively changing the content displayed in their field of view (FoV). Navigation is fundamental to various tasks performed by analysts using computational notebooks. Analysts frequently navigate between various parts of their analytical pipeline during exploratory data analysis to derive insights from data. Similarly, navigation is essential when taking over someone else's project to understand their process or when compiling a final re-

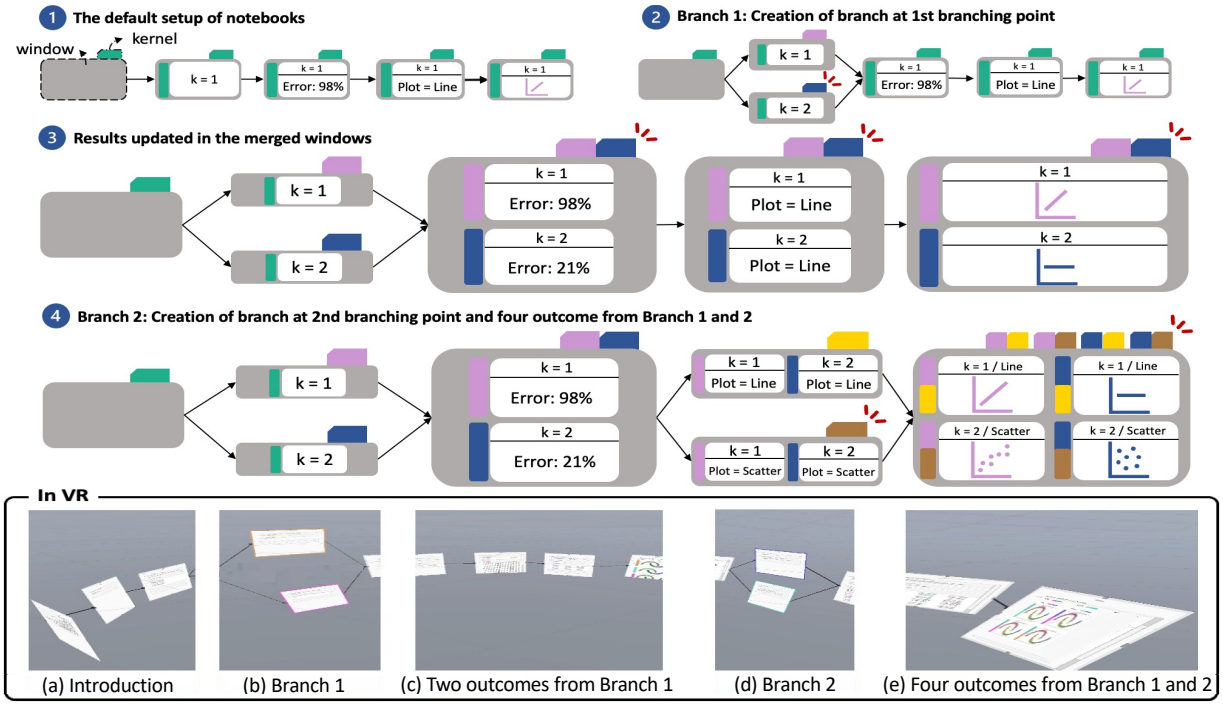



Figure 3.2: Visual representation (top) of the Branch&Merge mechanism within computational notebooks, as instantiated in a VR (bottom). Different hues within the results are employed to illustrate the independent storage of variables across branches. The figure is segmented into five key operations: (a) regular notebooks, (b) initial creation of the branch, (c) merge back to a singular code execution path, (d) initiation of the second branch, and (e) final merging process to facilitate value comparisons across all initiated branches.

port from the analysis conducted [45]. Building upon prior research [6, 54, 55, 56, 57], we define navigation as a multi-component process, primarily involving locating target sections and then moving towards them. With a conventional desktop computational notebook, it is challenging for analysts to recall the location of off-screen targets and accurately navigate ("scroll") to these locations. Therefore, our goal *is to enable analysts to quickly identify (locate) and reach (move to) their desired sections within the computational notebook in VR.*

**Comparing** outcomes derived from varying parameters or methods is a frequent task for analysts working with computational notebooks [58]. This process involves two stages: initially establishing the comparisons by coding tests for different parameters or methods, and subsequently examining the results to make informed choices regarding these parameters or methods. In the setting of traditional desktop computational notebooks, analysts typically rely on their memory for comparison tasks, externalize results for comparisons, write specialized code to produce multifaceted results, or replicate the notebook for comparison purposes. However, each of these methods has its limitations, either placing a significant cognitive load on the analyst's working memory or complicating the management of code and content. Consequently, our objective *is to enable analysts to intuitively generate comparisons and easily review all generated results.*

### 3.2.2 Adaptations

To investigate the advantages that VR could offer to computational notebooks, we designed and implemented adaptations that capitalize on VR's distinctive display and interaction features, with a focus on enhancing the *navigation* and *comparison* experiences. We specifically focused on facilitating physical navigation within the VR environment and enhancing comparison tasks through an embodied branch&merge gesture. Furthermore, we also developed other essential interactions tailored to the notebook's functionality in VR.

**Enabling Physical Navigation.** Physical navigation involves utilizing bodily movements, such as head rotation or walking, to explore an information space, like accessing various sections of a computational notebook. Research by Ball et al. [32] demonstrated that this form of navigation is more efficient than virtual navigation (pan and zoom) in the context of browsing geographic maps on large display walls. In VR, the ability to spatially arrange content offers a unique opportunity for physical navigation, which we anticipate could enhance notebook navigation compared to desktop versions. To establish an environment conducive

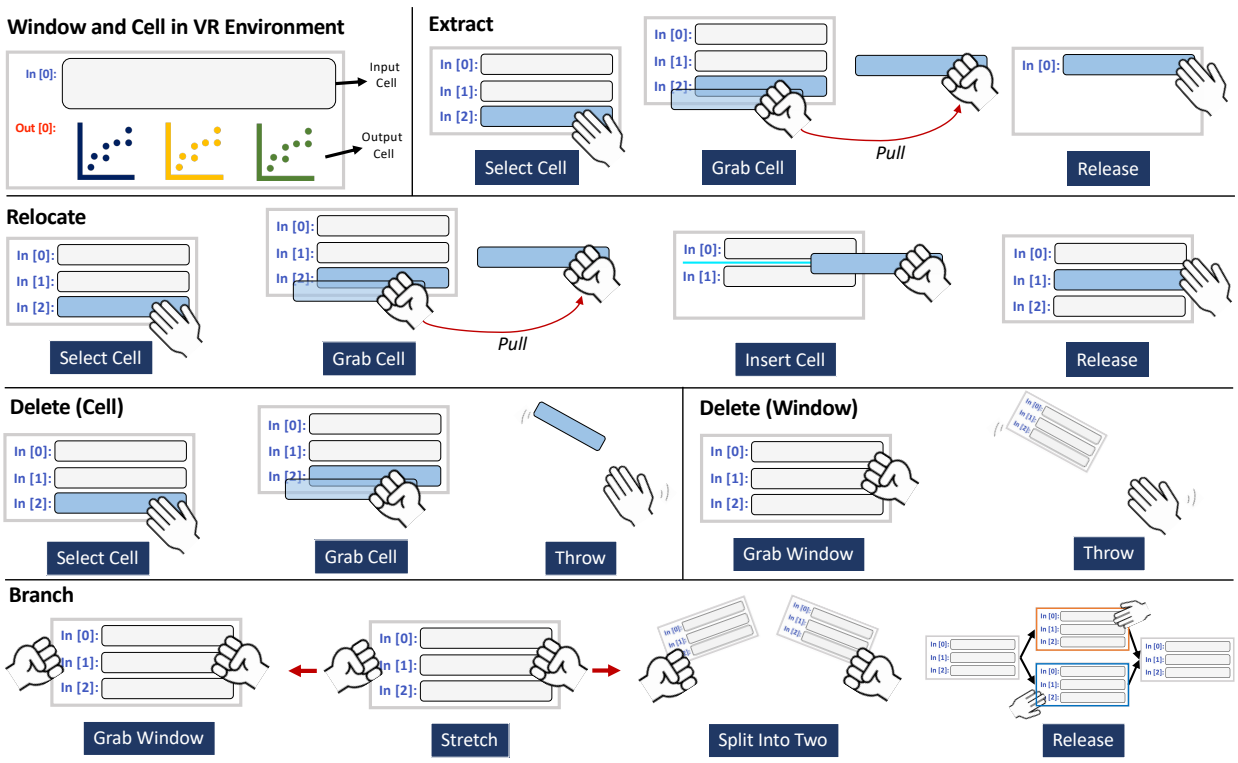



Figure 3.3: Illustrations of gestures interactions in the VR environment.

to physical navigation, we implemented the following adaptations.

*Adding one hierarchical layer.* Desktop computational notebooks employ a linear arrangement of cells and outputs within a singular window. Yet, transplanting this design directly to an immersive environment poses challenges. Extending the single window to accommodate all content could result in an impractically long display, potentially falling outside the user's reach. To convert a notebook into a suitable format for spatial distribution, we introduce an additional hierarchical layer to the content layout: cells and outputs are organized within individual windows, and these windows are interlinked to compose a complete notebook, see Fig. 3.1.

*Applying a curved layout.* Drawing on observations from Andrews et al. [59] regarding the layout of multiple windows, we adopted a commonly used horizontal window placement strategy. This linear arrangement, signified by directed arrows from left to right, not only clarifies the sequential order of windows but also ensures that all windows fall within the user's vertical reach. To optimize the curvature of this arrangement, we consulted Liu et al.'s findings [33, 60] for our initial layout placement, which indicate that a semi-circular layout generally surpasses both flat and full-circle configurations.

**Embodied Branch&Merge for Comparison.** In hypothesis testing via comparisons, analysts frequently employ the strategy of creating additional copies and modifying relevant content, such as adjusting a variable's value or invoking a different function, as highlighted by Weinman et al. [44]. In response, they introduced an interactive tool named "fork it," enabling users to create a concurrent copy with a button click. Adapting this interactive concept to immersive settings, we designed an embodied gesture for duplication: users grasp the window they wish to replicate with both hands and then stretch it until a specific threshold, as illustrated in Fig. 3.3—Branch. The user can freely place the newly created windows in space.

Our enhanced hierarchical structure in notebook content organization offers increased flexibility for hypothesis evaluation through non-linear branching. This enables precise content duplication at the window's granularity, as opposed to copying subsequent content, as seen in the "fork it" [44]. For instance, when an analyst intends to probe different predefined cluster values in K-means clustering, they can produce branches for various cluster assignments. The subsequent visualization code used to assess clustering results remains unduplicated. Moreover, our system supports branching at multiple points simultaneously, unlike prior systems

that were limited to single-point branching. For instance, consider having a linear notebook without any branch initially, illustrated in Fig. 3.2-❶. Subsequently, the user can create a branch at any point, as demonstrated in Fig. 3.2-❷. The creation of a branch leads to added results for comparisons in all the subsequent windows. The number of results is equal to the number of branched windows, say two, as depicted in Fig. 3.2-❸. Furthermore, the analyst can create another branch as demonstrated in Fig. 3.2-❹, and the subsequent window (only one last window in this case) will have four results produced by all combinations of the two branches.

**Additional Notebook Interactions.** Computational notebooks come with fundamental interactions for content management, such as creating, deleting, and moving cells, typically one cell at a time. Initially, we explored a toolbar-based design situated at the top of the window, mirroring the traditional desktop-based computational notebook interface. Nevertheless, our internal evaluations highlighted challenges with using a pointer for button interactions, confirming findings from previous studies [27, 61]. A recent study by In et al. highlighted the advantages of gesture-based interactions over the window-icon-menu-pointer (WIMP) design [30] in immersive settings. Consequently, we pivoted to designing intuitive gesture interactions for the immersive environment, which are also demonstrated in Fig. 3.3.

- *Extract*: Users can deploy a "grab & pull" gesture to detach a cell from its window, creating a new window for the selected cell. When extracting multiple cells, users can first select them and then employ the "grab & pull" gesture.
- *Delete*: To remove a cell, users can utilize the "grab & throw away" gesture. For multiple cells, after selection, the same gesture is employed. Entire windows can similarly be discarded with this gesture.
- *Relocate*: Users can "grab" a cell and "drag" it to a new position, whether within its initial window or to a different one. To relocate multiple cells, users should first select them and then execute the "grab & drag" action.

Additional interactions include "grab & move" for repositioning windows and "pinch-to-zoom" for resizing, where users collide their hands with a window and move them apart to enlarge or together to minimize. Beyond content and view adjustments, a single button on the user's left hand, inspired by Yang et al. [6], proved more efficient than attaching buttons to each window. This "Run" button executes the selected cell and all subsequent cells.

## 3.3 User Study and Evaluation

To systematically answer the research question, we designed and conducted a controlled user study. Primarily, our objective was to explore the potential advantages of utilizing an immersive environment. To this end, we compared our immersive computational notebook implementation with its Desktop counterpart. Additionally, we sought to enrich empirical evidence supporting the merits of the "branch&merge." In summary, our study encompassed four conditions: Desktop+Linear, Desktop+Branch, VR+Linear, and VR+Branch. These conditions enabled a systematic investigation of the effect of two variables: the computing environments (Desktop vs. VR) and the comparison techniques (Linear vs. Branch).

### 3.3.1 Study Conditions

Our Branch design in the immersive computational notebook (VR+Branch) is presented at Sec. 3.2—Branch&Merge. Meanwhile, our Desktop+Branch implementation shared a similar idea but utilized a button to duplicate a window instead of using an embodied gesture. On the other hand, the creation of branches was not permitted in both the Desktop+Linear and VR+Linear conditions. In the following, we detail our Desktop and VR implementations.

**Desktop**: In the Desktop environment, our design emulates the features and functionalities typical of standard computational notebooks, where interactions are facilitated via a mouse and keyboard. To navigate different segments of the notebook, we incorporated vertical scrolling, a standard navigation method in many Desktop applications. Users can navigate by using the mouse scroll or dragging the scrollbar. For other content interactions, we also follow the standard computational notebook designs: users use the mouse to select the target and click the buttons to execute specific commands, like extract, delete, and relocate. To ensure an equitable comparison and to control for potential confounders, we integrated features detailed in Sec. 3.2.

**VR**: We detail our primary computational notebook designs and implementations for VR in Sec. 3.2. This section focuses on vital design choices not strictly tied to computational notebook features. We opted for bare-hand interaction over using controllers, aiming for a more intuitive and immersive user experience.

However, text input remains a crucial aspect of immersive computational notebooks. Meta has pioneered a technology that brings physical keyboard tracking into VR [62], which we initially adopted. However, Meta's design primarily suits a seated work environment, as carrying and typing on a physical keyboard while navigating in VR is impractical. While Davidson et al. [50] proposed using a mobile table for the physical keyboard, their approach inadvertently tethered users to the table, reducing spatial exploration. To encourage fuller utilization of physical navigation in VR, we decided not to adopt their method, opting for the standard virtual keyboard method instead. Our first virtual keyboard implementation employed an "on-demand" approach, appearing during text interaction and vanishing when interacting with other elements. However, this approach was changed due to internal tests showing it often activated by mistake, leading to cluttering the interface. The revised design, inspired by Yang et al. [6], attaches the keyboard to the left palm, with improvements to prevent unintentional activations by requiring users to intentionally look at their palm to activate it.

In VR settings, interacting with distant windows presents a challenge for various text interactions. We selected a font size that ensured text readability from the initial viewing distance, eliminating the need for users to continuously adjust their proximity for code visibility. While the text remains readable from afar, pinpointing and selecting a precise point within the text, such as a specific entry, remains challenging. To facilitate precise interaction, we implemented a design inspired by Voodoo dolls [63], where a proximate copy of the interacting cell is generated for the user. Interactions between this close copy and the original notebook window are synchronized, as illustrated in Fig. 3.4 (c) and (d).

### 3.3.2 Task and Data

Computational notebooks are versatile tools that facilitate a wide range of analytical tasks, from creating new notebooks to utilizing existing code for data analysis. However, requiring participants to extensively write code from scratch in a controlled study could be time-consuming and introduce confounding factors outside the scope of our investigation. Meanwhile, it's increasingly common for analysts to revisit or leverage existing code, whether it's from inheriting someone else's project or reusing their previous work [64]. To maintain the focus of our study on the aspects of navigation and comparison, we simulated a scenario where participants were provided with pre-existing code.

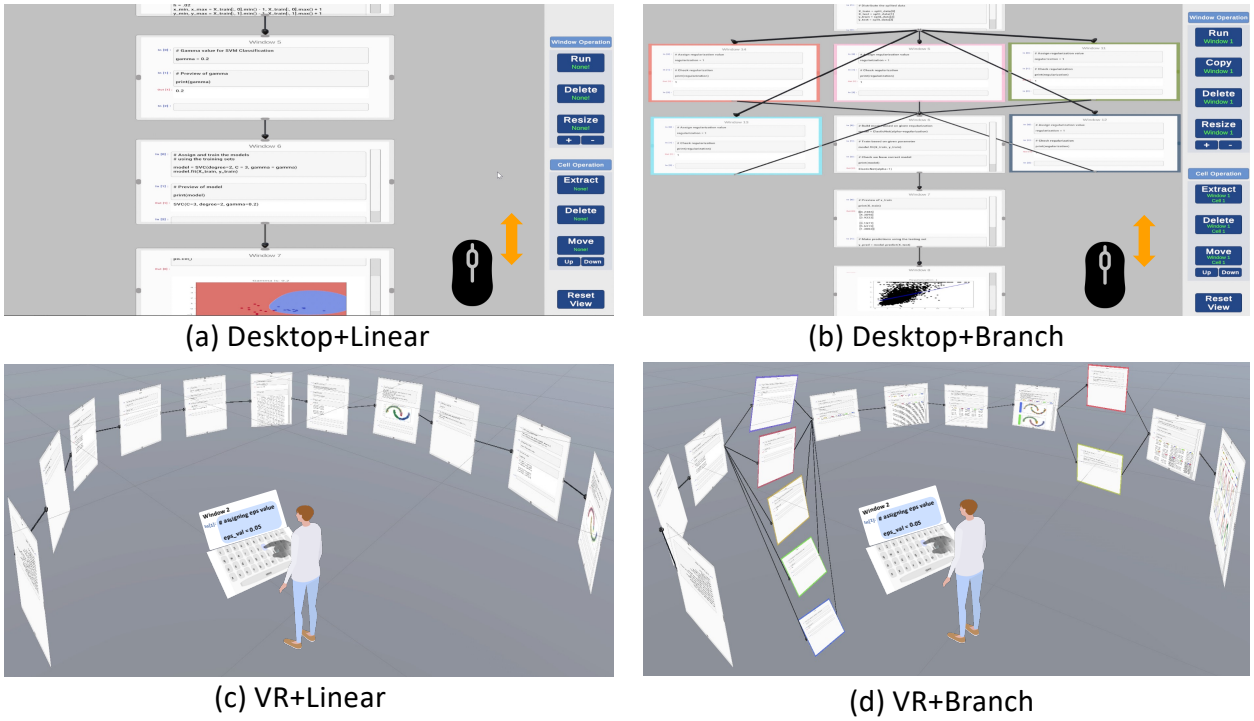



Figure 3.4: Demonstrations of conditions tested in our study. User scrolling to navigate in **Desktop** (top), and walking and rotating their body to navigate in **VR** (bottom). In addition, the user used a physical keyboard to write codes in **Desktop**, while used a virtual keyboard in **VR**.

We structured two tasks to evaluate the navigation and comparison performance within our test conditions. To mitigate any learning effects, each participant was presented with four analytical methods, assigning one method to each test condition: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Linear Regression. As mentioned, the order was determined by a balanced Latin square matrix. The computational notebooks used in the study were sourced from the official scikit-learn documentation [65]. These notebooks were standardized to approximately ten windows each, based on internal testing that showed our chosen length allowed for practical task completion times. Moreover, the notebooks exhibited a consistent logical structure: they initiated with data loading, data transformation, modeling, and concluding with the visualization of model outcomes. Details of the specific study tasks, formulated within this overarching context, are presented subsequently. Supplementary materials containing all study stimuli are provided.

**Task 1. Navigation.** To assess the performance across different types of navigation, we designed tasks that involved both single-stop and multi-stop (specifically, two-stop) navigation scenarios. The single-stop task had participants identify and delete an error-causing cell called *deletion*, while the two-stop task involved identifying and correctly repositioning a misplaced cell called *relocation*. Participants could identify these target cells by inspecting the cells' output; notably, cells generating errors and their subsequent cells would not yield output. This task was designed to be navigation-intensive, enabling us to extract nuanced differences in performance and user experience related to navigation activities. Consequently, our primary aim was to investigate the impact of computational environments—**VR** vs. **Desktop**—on navigation efficiency and user experience.

**Task 2. Comparison.** Following Task 1, we introduced Task 2, designed to simulate real-world hypothesis testing. Participants evaluated two parameters within various analytical methods, such as cluster numbers and distance metrics in the KNN method, to determine the optimal parameter combinations based on the visualized results. To ensure consistent experimental conditions, we standardized the spatial distance of relevant windows (i.e., the two windows containing "what-if" tests and the result window) across all trials. Minimal text input was required from participants due to pre-commented code, simplifying the process of parameter adjustment. Although our primary focus was on comparison, navigation was inherently involved in task completion.

### 3.3.3 Experimental Setup

In the VR configuration, we utilized the Meta Quest Pro headset, providing a resolution of 1800 × 1920. For DESKTOP conditions, a standard 27" monitor was deployed, featuring a 2560x1440 resolution. The Meta Air Link feature was used for the VR environments, enabling a tether-free experience by leveraging the PC for computations while the headset managed to render. This configuration allowed participants to freely navigate the $16m^2$ space without worrying about cable impediments. Within the VR setting, participants started at the center of the space, presented with ten notebook windows, each measuring $0.35x0.30m^2$, arranged semi-circularly at a distance of $1m$. Conversely, DESKTOP participants sat at a desk, encountering initial notebook windows followed a linear structure and sized at on average 2000 × 600 pixels each. Specifically, the notebook windows were displayed on the center of the monitor, allowing participants to view two or three notebook windows at the same time. Additionally, for the DESKTOP+BRANCH, we left empty spaces on both the left and right sides of the notebook windows to ensure sufficient space for branching. This arrangement was mirrored in the DESKTOP+LINEAR to ensure consistency across the study settings, as shown in Fig. 3.4 (a) and (b).

### 3.3.4 Participants

We recruited 20 participants (16 male, four female, ages 18 to 35) from a university mailing list. The recruitment was based on their knowledge of data science and machine learning algorithms, which was screened using an eight-question quiz (provided in the supplementary material). Participants need to answer six out of eight to be eligible for the study. Out of the 22 respondents, 20 were invited to participate in the study based on the eligibility requirement. Regarding VR experience, seven of the participants use VR weekly, and the remaining thirteen have no prior VR experience. All participants had either normal vision or vision corrected to normal. For their time and contribution to the study, each participant was compensated with a $20 Amazon Gift Card.

### 3.3.5 Design and Procedures

Our user study followed a full-factorial within-subjects design, with conditions balanced using a Latin square (4 groups). The study, on average, took less than two hours. Participants were initially welcomed and reviewed a consent form. Then, we briefly introduced the study's objectives and procedural steps. Following this introduction, participants proceeded to the various components of the study as follows:

**Preparation**: We asked participants to adjust the chair height to a comfortable level for the Desktop condition and adjust the Quest Pro headset for the VR condition before they started the training session. We confirmed that all participants were in comfortable conditions and could see the text in all display environments clearly.

**Training**: We initiated our study by standardizing computational notebook terminologies, recognizing the potential for varied interpretations. The training was provided only when participants first encountered a computing environment (i.e., Desktop or VR). This was due to the consistent operational logic within each environment, with differences only in the comparison task. In the training, participants viewed operational demonstration videos. Post-viewing, we verified their understanding, asking them to replicate study tasks using a different algorithm, k-mean. Participants were free to inquire about operations or tasks. The training sessions, particularly for the VR condition, were extended to give participants enough time to become comfortable with the immersive environment. This approach was adopted to address potential VR-related issues such as discomfort, learning effects, and novelty bias. In summary, the training was completed once participants achieved proficiency in tasks and operations, which generally took 10-15 minutes.

**Study Task**: Upon completion of the training session, participants proceeded to the study task. To ensure they had enough understanding of what would be expected, we provided comprehensive context, including a brief explanation of the algorithms and the tasks they needed to complete. Participants had no time limit for task completion but were encouraged to prioritize accuracy and efficiency. For the VR environment, we reset the participants' position to the center of the room and had them face the same initial direction before each study task started.

**Questionnaires**. *Post-Condition Questionnaires*: upon completion of each condition, participants were required to fill out a Likert-scale survey. This was adapted from the System Usability Scale (SUS) and NASA Task Load Index (TLX) to record their subjective experi-

ences. Additionally, they were asked to provide qualitative feedback concerning the pros and cons of the condition they had just interacted with. *Post-Study Questionnaires*: Once all the study tasks and post-condition questionnaires were completed, participants were asked to rank the study conditions based on their overall experience.

### 3.3.6 Hypotheses

We aimed to validate whether our designs and implementations met our established design goals. Consequently, we formulated hypotheses grounded in empirical findings from prior research and the testing conditions described in Sec. 3.3.1.

**Navigation in VR and on Desktop ($H_{nav}$).** We hypothesized **VR** would provide faster navigation than **Desktop**. **VR** offers a large display space to lay out an entire notebook, allowing participants to navigate by physically walking in the space or rotating their heads. In contrast, **Desktop** presents only part of a notebook at a time, requiring participants to scroll up and down for navigation. Previous studies indicate that physical navigation—employed in our **VR** conditions—is more effective than virtual navigation, as used in **Desktop** conditions [32]. Furthermore, **VR** has been demonstrated to enhance spatial awareness, thereby aiding in the recall process during multi-stop navigations [7, 66]. We believe these established advantages of **VR** are generalizable to computational notebooks.

**Comparison with and without Branch ($H_{comp-branch}$).** We expected that the incorporation of the **Branch** feature would facilitate comparison tasks. Earlier studies have reported favorable user experiences with similar functionalities in computational notebooks [44, 67]. Building on these insights, we introduced additional features, such as merging post-branching, to minimize visual clutter and spatially organize results. We aim to provide quantitative empirical data to highlight the effectiveness of the **Branch** functionality.

**Comparison in VR and on Desktop ($H_{comp-env}$).** We anticipated that **VR** could outperform **Desktop** in performing comparisons. In the **Linear** conditions of **Desktop** and **VR**, the comparison would be intrinsically linked to the navigation efficiency, as participants would only view one result at a time in both conditions. Given this, the navigational advantages of **VR** are expected to positively impact comparison tasks in **Linear** conditions. For the **Branch** conditions, we considered our designed **VR** embodied gesture for branch creation would be intuitive, thereby facilitating the process. Moreover, the large display space in **VR**

could allow participants to view all results simultaneously, expediting the visual assessment process.

### 3.3.7 Measures

In our study, we gathered quantitative data to evaluate our hypotheses. For the navigation task, we logged the *time* taken by participants to complete one-stop (deletion) and two-stop (relocation) navigations under each condition. *Completion times* for the comparison task were also recorded, as was the frequency of "Run" button presses, indicating execution. For potential subsequent analyses, we also logged user interaction and tracked objects in the scene.

After participants engaged with a specific condition, they were asked to complete a survey using a 7-point Likert scale to gauge their perceived *physical* and *mental demands*, *engagement*, and the *effectiveness* of that condition. To further explore the nuances of each condition, semi-structured interviews were conducted, highlighting both strengths and areas for improvement for each condition. Concluding the study, participants provided an overall ranking of their user experience within the testing conditions.

## 3.4 Results

In this section, we present the statistical analysis of our collected data, outline the strategies participants employed to manage the display space, and provide summarized qualitative feedback for each condition. We documented significance at levels of $p < 0.001(***)$, $p < 0.01(**)$, $p < 0.05(*)$, and $p < 0.1(\cdot)$. Additionally, we present mean metrics with a 95% confidence interval (CI) and use Cohen's d to determine the effect sizes of significant differences. Comprehensive statistical analysis results can be found in the supplementary materials.

### 3.4.1 Quantitative Results

All participants successfully completed the study tasks, resulting in no variance in accuracy metrics. In the rest of this section, we present results from other measurements that highlight

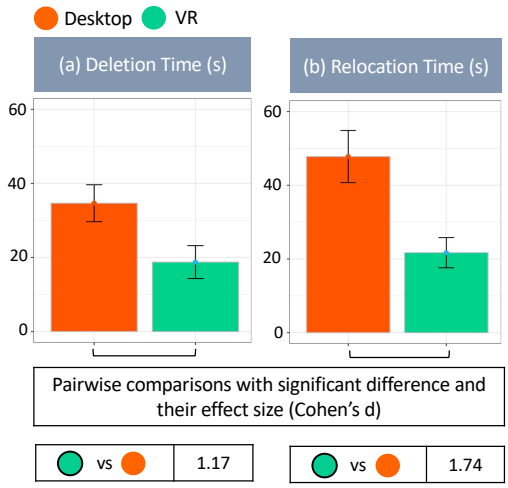



Figure 3.5: Completion time for **VR** and **Desktop** in the navigation task. (a) the time spent for completing deletion, and (b) the time spent completing relocation. Solid lines indicate statistical significance with $p < 0.05$. The tables below show the Cohen's D effect sizes for significant comparisons. Circles with black borders indicate the condition with better results.

performance differences among the conditions.

**Completion time for the navigation task.** The computing environment significantly influenced the time taken for deletion (one-stop navigation) and relocation (two-stop navigation), with both $***$. On average, **VR** only required nearly half the time compared to **Desktop**, exhibiting statistical significance and large effect sizes. To be more specific, **Desktop** witnessed a considerable 38.0% increase in completion time (from avg. 34.7s to avg. 47.8s) between deletion and relocation, **VR** exhibited only a 15.7% increase (from avg. 18.8s to avg. 21.7s) (refers to Fig. 3.5). Consequently, we accept $H_{nav}$.

**Completion time for the comparison task.** We found that having the branching feature had a significant effect on time and execution number ($***$), and the interaction of the computing environment and having the branching feature also had a significant effect on time and execution number ($***$). We did not find the computing environment had a significant effect.

**Branch** conditions were significantly faster than **Linear** conditions, for both **VR** and **Desktop** ($***$), with large effect sizes, see Fig. 3.6 (a). Additionally, having **Branch** also significantly reduced the number of executions required for both **VR** and **Desktop**, with large effect sizes, see Fig. 3.6 (b). Thus, we accept $H_{comp-branch}$. On the other hand, we did not observe




Figure 3.6: Analysis of four testing conditions in the comparison task. (a) the time spent completing the task, (b) the number of executions performed, (c) the time spent for text input, (d) the time spent completing the task excluding the text input interaction time, (e) the total time spent for creating all branches in Desktop and VR, (f) the average time spent for creating a branch in Desktop and VR. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $0.05 < p < 0.1$. The tables below show the Cohen's D effect sizes for significant comparisons. Circles with black borders indicate the condition with better results.

VR outperforming Desktop in the comparison task. In fact, VR+Branch took longer than Desktop+Branch. Therefore, $H_{comp-env}$ cannot be accepted.

**Text input time analysis.** In our observations, we noted that participants devoted a considerable amount of time to text input within the VR environment, despite our efforts to streamline and enhance the text input experience, as outlined in Sec. 3.2. To systematically understand this influence, we analyzed the duration dedicated to text input across all test conditions. We discovered that the VR conditions necessitated significantly more time for text input compared to the Desktop conditions ($***$), with VR+Linear taking more time than VR+Branch ($***$)—both findings having large effect sizes. On average, text input consumed 144.3s, or 29.5% of the total time, for VR+Linear, and 79.3s, or 27.1% for VR+Branch. In contrast, desktop scenarios required a mere 7.2s (1.6%) for Desktop+Linear and 5.9s (2.3%) for Desktop+Branch, as shown in Fig. 3.6 (c). This data validates our observations, highlighting that text input in VR significantly hindered performance.

In a subsequent post hoc analysis, we excluded text input durations from all conditions and re-conducted the analysis, refer to Fig. 3.6 (d). The results suggested that VR+Linear was faster than Desktop+Linear, with a medium effect size and statistical significance ($**$). Although there appeared to be a trend with VR+Branch outpacing Desktop+Branch, this distinction was not statistically significant.

**Branch creation efficiency.** To further investigate the performance differences between Desktop+Branch and VR+Branch, we examined the time taken for branch creation in both Desktop and VR environments, where we consider the total time of creating and placing branch windows, as illustrated in Fig. 3.6 (e, f). This analysis encompassed the duration required for both the creation and positioning of the newly created branches. Our findings indicate that branch creation in VR+Branch was notably slower than in Desktop+Branch ($***$), exhibiting a large effect size.

**Ranking and ratings.** Participants significantly favored the Branch conditions over the Linear conditions ($***$), as depicted in Fig. 3.7. Among them, VR+Branch was most frequently cited as offering the best overall experience, with 80% of participants placing it first. In contrast, 20% of participants ranked Desktop+Branch as their top preference, and no participants considered Linear conditions as their most preferred condition.

Significant effects were also observed across all perceived metrics: *physical demand* ($***$), *mental demand* ($***$), *engagement* ($***$), and *effectiveness* ($***$). Branch conditions

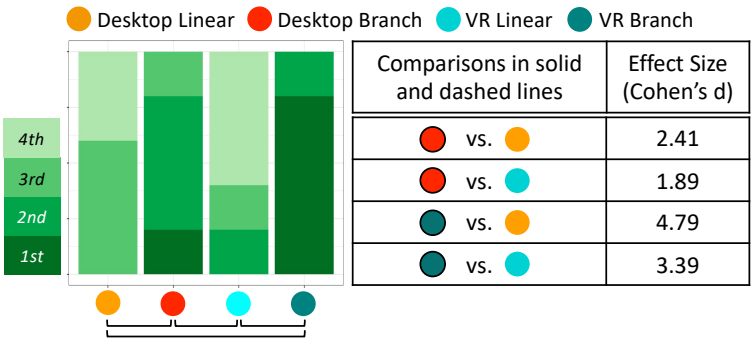



Figure 3.7: User ranking of overall user experience. Solid lines indicate significant differences with $p < 0.05$. The tables on the right show the Cohen's D effect sizes for significant comparisons. Circles with black borders indicate the condition with better results.

outperformed Linear conditions in terms of mental demand ($***$), engagement ($***$), and effectiveness ($***$), all exhibiting large effect sizes. Moreover, VR conditions were found to be more physically demanding than Desktop conditions ($***$). VR+Branch emerged as the most engaging condition, boasting an average rating of 6.65 out of 7 with a confidence interval of 0.46. Impressively, 85% of participants awarded it the highest engagement score.

### 3.4.2 Layout Strategies

To better understand how participants utilized the display space, we analyzed the final layouts of each trial to understand participant strategies in Desktop and VR settings, with detailed collections available in the supplementary materials.

Within the Linear conditions, we observed a limited number of layout-related interactions. Notably, in Desktop+Linear, the vast majority of participants refrained from repositioning or resizing windows. Meanwhile, in VR+Linear , certain alterations to the initial layout were made: eight participants expanded the last result window, while two relocated select "key" windows—namely, those containing cells crucial for generating comparisons, and the result window itself.

In contrast, the Branch conditions manifested a wider array of layout strategies, especially in terms of the placement of newly created branching windows. Within the Desktop+Branch condition, a dominant group of participants (15) arranged branching windows in a grid pattern. Initially, many aimed for a horizontal alignment, but due to spatial constraints, opted for additional rows, as depicted in Fig. 3.9 (a). The other five participants chose

a vertical layout, establishing a secondary column, as illustrated in Fig. 3.9 (b). In **VR+Branch**, similar to **VR+Linear**, numerous participants enlarged and/or relocated particular "key" windows. Within the large display space in **VR**, positioning of all branching windows could be orthogonal to the initial setup direction, eliminating overlap between connecting lines and windows—a choice made by 13 participants, showcased in Fig. 3.9 (c). Meanwhile, seven participants opted to conserve vertical space, forming an extra column within a grid layout, displayed in Fig. 3.9 (d).

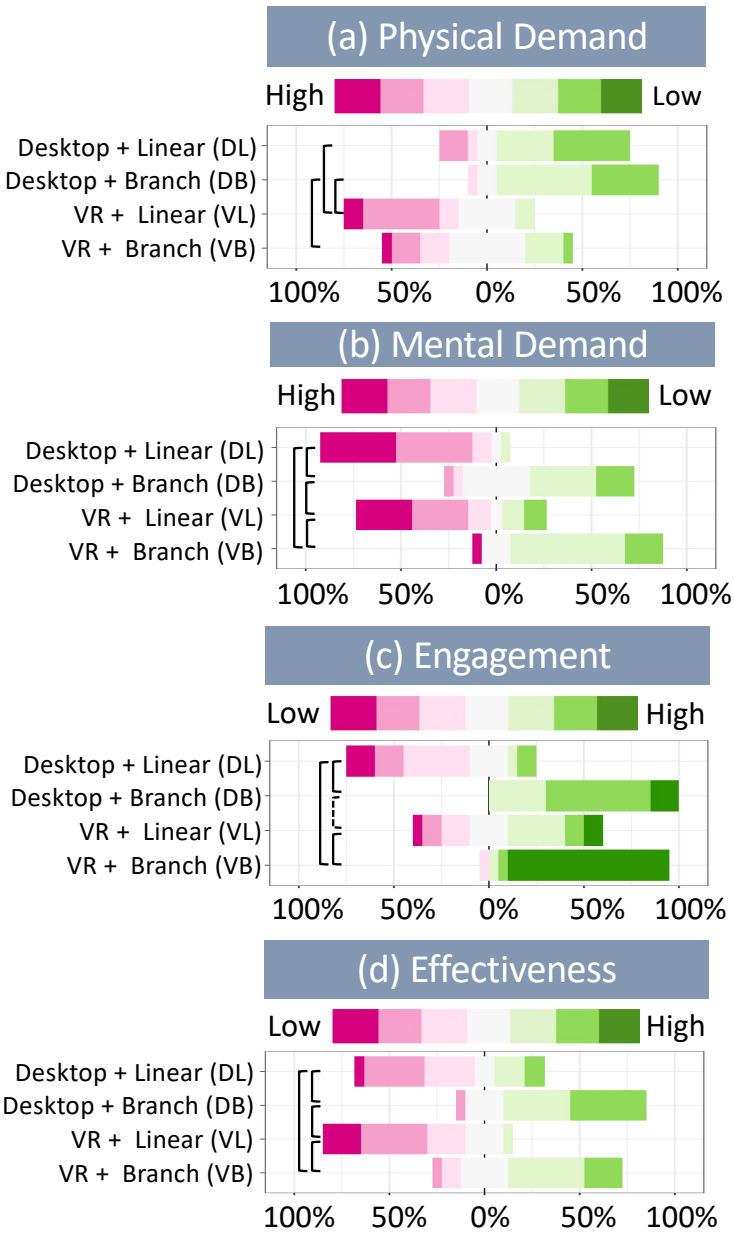
### 3.4.3 Qualitative Feedback

We conducted a qualitative analysis to identify common themes in user feedback for each condition. To systematically interpret our collected feedback data, two authors formulated a coding scheme rooted in the first five participants' feedback, which was subsequently applied uniformly to subsequent participants. The top three codes and those mentioned by participants more than five times were reported for every condition (with frequency shown in parentheses). We concluded by summarizing the overarching insights gleaned from all the conditions. Comprehensive coding results are available in the supplemental materials.

**Desktop + Linear** described favorable opinions with distribute cells into *multiple windows are better than a single document* (7) and *familiar* to typical computational notebook applications (4). However, drawbacks were noted, with concerns such as the need to *scroll a lot* (14), *text and target objects are hard to find* (8). These issues lead to *inhibit task performance* (5).

**Desktop + Branch** was considered positively, with *easy to compare* the results of different parameter values (18), *scroll less* (6), and *fast* to perform comparisons (6). With the integration of the branch and merge feature, participants found it to *lower the mental demand* and serve as an *effective fine-tuning* method, according to three users. However, some concerns were also noted, including that *the initial linear layout is not effective* (9), and *target objects were hard to find* (6).

**VR + Linear** was praised for its inclusion of gesture interaction and physical navigation, with descriptions such as *intuitive* (12), *easy navigation* (9), and more *fast* and *effective* than WIMP (7). Participants also found it *easy to understand the code* (7). On the other hand, major issues were related to the *text input difficulty* (14), with users stating that the provided




| Comparisons in solid and dashed lines | Effect Size (Cohen's d) |
|---|---|
| **DL** vs. VL | 1.37 |
| **DB** vs. VL | 2.13 |
| **DB** vs. VB | 1.37 |
| **DB** vs. DL | 2.47 |
| **DB** vs. VL | 1.45 |
| **VB** vs. DL | 2.65 |
| **VB** vs. VL | 1.60 |
| **DB** vs. DL | 2.38 |
| **DB** vs. VL | 1.25 |
| **VB** vs. DL | 2.81 |
| **VB** vs. VL | 1.75 |
| **DB** vs. DL | 1.39 |
| **DB** vs. VL | 2.22 |
| **VB** vs. DL | 1.04 |
| **VB** vs. VL | 1.79 |

Figure 3.8: Subjective ratings on (a) physical demand, (b) mental demand, (c) engagement, and (d) effectiveness by task. Towards the right end of subfigures means better-perceived results. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $0.05 < p < 0.1$.

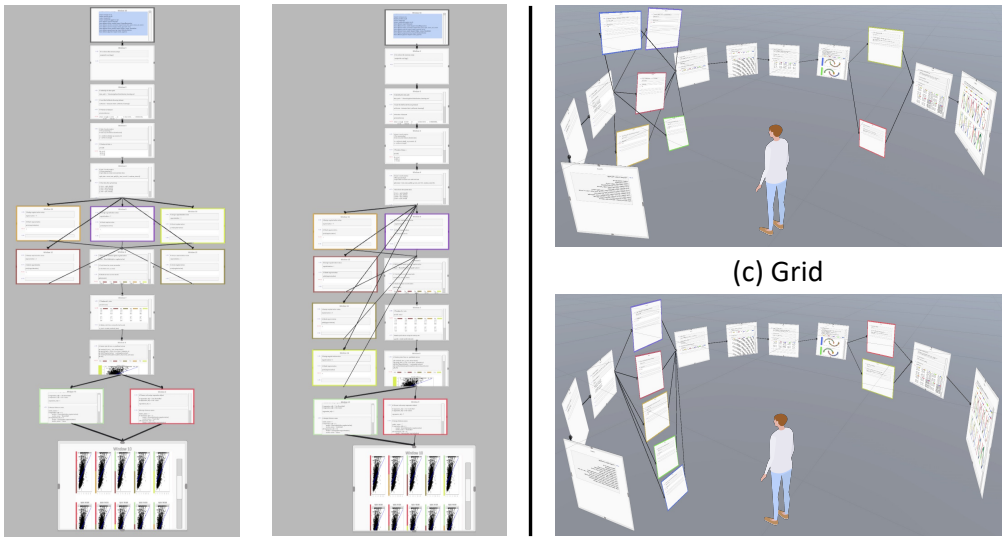



Figure 3.9: Two layout strategies used by our participants in Desktop+Branch(Left) and in VR+Branch(Right).

virtual keyboard was challenging to interact with.

VR + Branch, similar to VR+Linear, was considered as *intuitive* (11), characterized by an *effective initial layout* (11), and *easy to understand the code* (4). It also demonstrated that the system provided a *easy to compare* (9), *easy navigation* (9), and was *fast* to identify the optimal result (8). Unlike Desktop+Branch, participants in this condition described it as *easy to organize* (8), with a *large display place* (7), and found managing windows to be very *flexible* (4). Notably, no specific navigation issues were identified while performing tasks in VR+Branch.

## 3.5 Findings and Discussions

Our primary objective is to validate the advantages of VR over the conventional desktop computing environment. While there's a growing interest in integrating VR/AR into data analytics, as highlighted in a recent state-of-the-art report [3], empirical studies directly contrasting VR with traditional environments remain limited. Accordingly, our research seeks to offer empirical insights into both the performance and user experience distinctions between VR and Desktop in the context of computational notebooks. We also aim to

present quantitative data regarding the efficacy of our refined "branch & merge" design. Our subsequent findings and discussions will center on these two focal areas.

### 3.5.1 Is VR beneficial?

Our study results reveal that VR markedly surpassed Desktop in the navigation task. However, this advantage did not extend to the comparison task, primarily due to VR's inefficient text input mechanism.

**In terms of *navigation*,** participants operating within VR completed tasks faster than those using Desktop, both for deletion (one-stop navigation) and relocation (two-stop navigation). During one-stop navigation, participants scanned and traversed the notebook windows to locate a target. In the VR environment, this often involved head rotation, whereas in the Desktop environment, mouse scrolling was performed. Data suggests that physically rotating the head is more efficient than employing a mouse for navigating expansive information spaces that exceed the display size. This finding aligns with a study by Ball et al. [32], which demonstrated the efficiency of physical navigation.

We also intentionally tested a two-stop navigation, where we still found VR to be faster compared to Desktop. Participants, during this portion of the task, first located a target and subsequently repositioned it. We anticipated that the consistent spatial environment in VR enhances participants' spatial recall, allowing them to identify the second target more efficiently than in Desktop. This would lead to a relatively smaller increase in completion time and ratio. Our reasoning aligns with prior research that examined the efficacy of spatial memory within VR [7, 66].

*In summary, for navigation,* we found that VR outperformed Desktop within computational notebooks, largely attributed to its accelerated browsing speed and enhanced spatial awareness and memory.

**In terms of *comparison*,** however, the pattern shifted. While Desktop+Linear and VR+Linear exhibited comparable completion times, VR+Branch lagged behind Desktop+Branch. As delineated in Sec. 3.4.1, we foresaw—and subsequently confirmed—that challenges associated with text input considerably impacted the performance under VR conditions. After accounting for text input durations, VR+Linear significantly outperformed Desktop+Linear, utilizing its navigational strengths. In the Linear conditions, the effec-

tiveness of comparisons was closely tied to navigation efficiency since participants could view only one result at a time. However, the physical navigation capabilities of VR had a positive effect on comparison tasks in these conditions. For the Branch conditions, the use of an intuitive VR gesture for creating branches was designed to make the process easier. Additionally, the larger display area offered by VR allowed for the simultaneous viewing of all results, which expedited the process of visual evaluation. Yet, VR+Branch only slightly edged out Desktop+Branch, not fully capitalizing on its navigational strengths.

Delving deeper into underlying factors, we concentrated on elements of the task not inherently tied to navigation. A detailed analysis of our interaction data unexpectedly revealed that participants took, on average, twice as long to generate a branch in VR compared to Desktop, see Fig. 3.6(e and f). We hypothesize that this increased duration is attributable to the extended physical movements required by VR's gestural interface, a notion supported by Fitts's law given the greater overall movement distance in the VR environment. Additionally, we observed specific behavioral patterns among participants using VR. Typically, they would first grasp the window, retreat a step to initiate the branching process, and then advance to position the resultant windows. This step-back-and-forward motion appears to be a deliberate strategy to prevent the new branch windows from colliding with existing notebook windows, while also maintaining a consistent depth of window placement in space. These additional interactions and subsequent fine-tuning of window positions incurred further time penalties in VR. Such findings are consistent with previous studies that have reported similar observations [30, 68, 69]. Nevertheless, it's worth noting that despite the additional time required for the comparison task, participants expressed a clear preference for VR's embodied interaction design, which received the highest ratings for both overall user experience and engagement.

*In summary, for comparison,* VR maintains its navigational advantage, as navigation remains a crucial element in this task. However, the system's inefficiency in text input negatively impacted its overall performance. Additionally, although the embodied gesture interface in VR enhances user experience, it comes at the cost of increased task completion time.

### 3.5.2 Is "branch & merge" beneficial?

Yes, in our analysis, we found that the introduction of the Branch feature considerably shortened the completion time for comparison tasks in both VR and Desktop. Additionally,

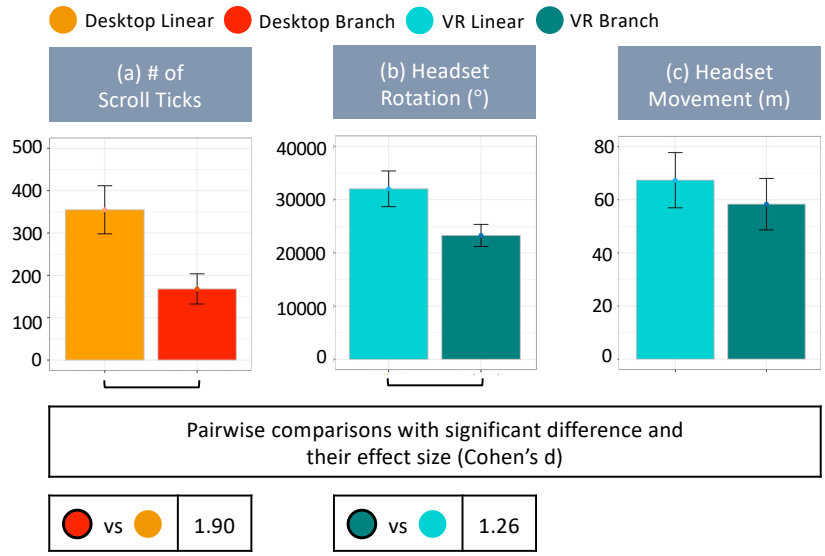



Figure 3.10: Navigation distance of different navigation methods across **Desktop** and **VR**: (a) the number of scroll ticks on the **Desktop**, (b) the degree of head rotation, and (c) the distance traversed in **VR**. Solid lines indicate statistical significance with $p < 0.05$. The tables below show the effect sizes for pairwise comparison. Circles with black borders indicate less navigation distance required.

participants evidently perceived the **Branch** feature positively in terms of *mental demand*, *engagement*, and *effectiveness*, as well as the *overall user experience ranking*. This subjective feedback aligns closely with findings from Weinman et al. [44], wherein participants rated a similar desktop "branch" implementation. Our contributions extend this understanding by providing quantitative measures: for the comparison task in our study, the "branch & merge" feature nearly reduced half of the completion time compared to its absence. Although creating a branch may initially take extra time, incorporating features like merging after branching can significantly reduce visual clutter and organize results spatially. This approach greatly decreases the amount of navigation effort needed. Further post hoc analysis of the navigation methods in **Desktop** and **VR** validated our observations: both mouse scrolling and head rotation distances were notably shorter in **Branch** than in **Linear** as shown in Fig. 3.10. To conclude, the "branch & merge" feature enhances the comparison process, and our study presents no evident drawbacks related to its use.

## 3.6 Conclusion

We adapted the computational notebook interface from desktop to VR and tested its effectiveness through a controlled study. Our results revealed that notebooks in **VR** outperformed notebooks on **Desktop** in navigation efficiency, and the inclusion of a "branch & merge" feature notably enhanced the non-linear comparison process. Participants reported that the integration of VR with the "branch&merge" functionality was the most engaging and provided the best overall user experience among all test conditions. However, we observed that text interaction in VR remains a challenge. This issue could be alleviated with future advancements in hardware and tracking technologies, and as users become more familiar with VR environments over time. Our study underscores the immense potential of computational notebooks in VR, particularly in enhancing navigation and comparison performance and experience for analysts. It's important to note that our VR adaptation was specifically tailored to investigate navigation and comparison, and there may be other innovative approaches for adapting or completely redesigning computational notebooks in VR. Broadly, our results provide preliminary evidence supporting the wider use of large display spaces, augmented spatial awareness, embodied interaction, and physical navigation in VR for immersive analytics applications.

# Chapter 4

# Embodied Data Transformation

## 4.1 Introduction

Data transformation is a data science process that converts a data set into the desired format to enable subsequent data science tasks, like visualization and modeling [9]. It is well recognized that data scientists need to spend an excessive amount of time doing data transformation, making it essential but also the most tedious and time-consuming aspect of a data science project [70, 71]. Using a programming language, like SAS, R, or Python, is the standard way of performing data transformation. However, as data science becomes ubiquitous and exposed to people with limited programming knowledge, the prerequisite of knowing to program makes data science inaccessible to a large group of professionals whose workflows involve data [72], which we called *non-technical data workers*. As a result, the back-and-forth communications caused by data science's iterative and open-ended nature can heavily inhibit insight discovery and decision-making.

In response, like in many other data science processes, there is an increasing trend of providing user interface-based (UI-based for short) tools for data transformation (e.g., Tableau [73] for visualization and AutoML [74, 75] for modeling). These UI-based tools lower the entry barrier for data science and also help reduce errors [76]. However, even though there exist several commercial UI-based data transformation tools (e.g., Tableau Prep Builder [24], Trifacta [25], and Alteryx [26]), the field lacks an empirical understanding of people's experiences in using these tools and the considerations in designing them. Moreover, while the WIMP (windows, icons, menus, pointer) metaphor is typically used for constructing UI-based tools, modern interaction techniques that allow direct manipulation of the visual elements in the same space (named *embedded interaction*) [77, 78] were found to be more time-efficient in specific scenarios, like manipulating visualizations [79, 80]. Most notably, Kandel et al. [70] and Nandi et al. [27, 28, 29] found their UI-based tools to be more effi-

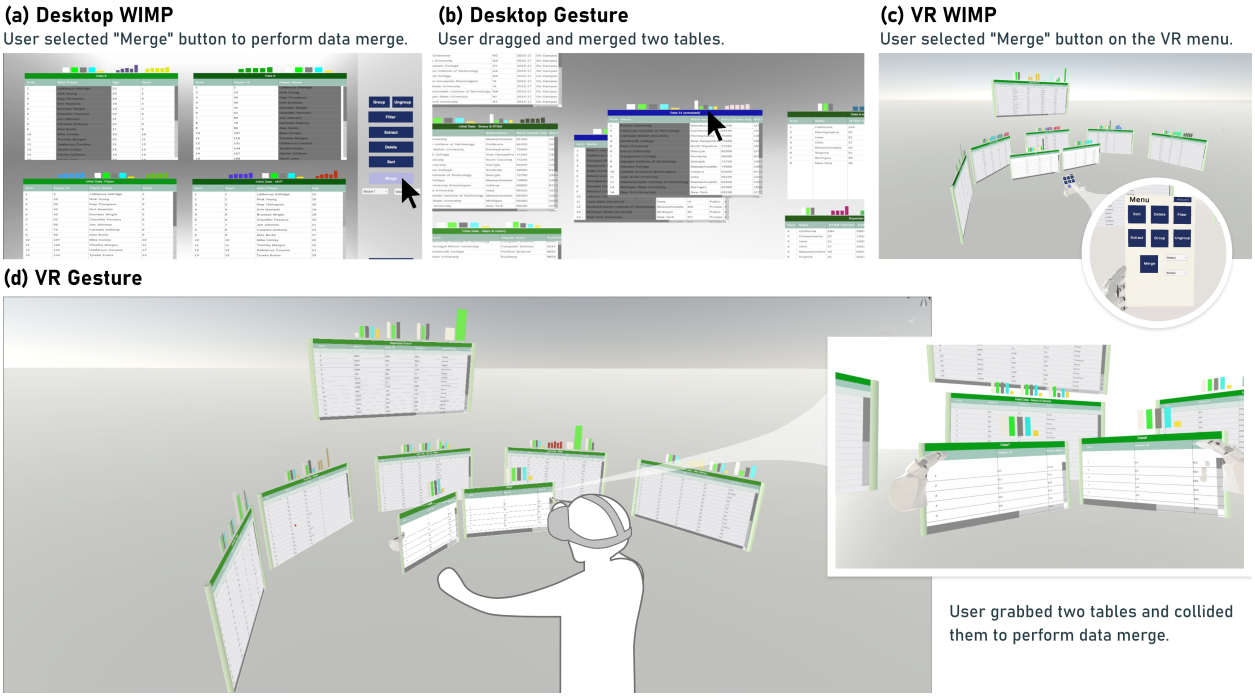



Figure 4.1: Four conditions designed for performing data transformation in the user study, including a combination of desktop or VR environments, and WIMP or gesture interactions.

cient in low-level data transformation tasks. However, it is unclear if their findings can be generalized to more realistic and complicated scenarios. **Our first goal** is to investigate the potential benefits of embedded interaction techniques over traditional WIMP interfaces in more realistic data transformation tasks.

On the other hand, in addition to interaction techniques, the rapidly evolved display and interaction environments (e.g., virtual and augmented reality or VR/AR) offer tremendous opportunities for creating innovative human-computer interaction experiences. Specifically, there is a growing interest in using VR/AR for data analysis, bringing an emerging research topic — Immersive Analytics [3, 4]. From recent studies, there are two most frequently reported motivations for using VR/AR in analytics: *large display space* [6, 34, 81, 82] and *embodied interaction* [8, 83, 84]. We believe there is great potential to explore whether those identified benefits can be generalized in improving the data transformation workflow. On the other hand, standard mid-air methods in VR/AR are not suitable for tasks requiring high-precision interactions [19, 85], which could be inevitable in some data transformation tasks. Therefore, **our second goal** is to investigate how these identified pros and cons can affect data transformation tasks in immersive environments.

Data science is iterative by its nature and does not follow a sequential pipeline. Consequently, alternating between different steps is inevitable [9]. For example, after observing some visualizations, analysts may need to perform extra data transformations for the next analysis iteration. Although visual exploration (e.g., ImAxes [8] and DataHop [86]) is feasible in a fully immersed manner, there is no immersive data transformation tool (i.e., tools for explicitly changing data table formats). When analysts want to use immersive visualization, they have to switch between VR and desktop to complete the iterative data science tasks, causing high overhead for context-switching. To this end, we study immersive data transformation tools to progress to a future where analysts can be fully immersed in VR for the entire data science workflow and maximize the benefits of the next generation of display and interaction environment.

To close these gaps, we developed prototypes with embedded interactions on the desktop and embodied interactions in VR for non-technical data workers to support essential data transformation operations. Compared to a standard WIMP user interface, users can directly manipulate data tables through mouse or physical gestures (e.g., overlay one table on top of another to *merge* them, see Fig. 4.1). We compared our interaction designs to WIMP for desktop and VR. To best simulate real-world scenarios, instead of testing low-level tasks, we asked participants to transform a set of data tables into a target format. We found that participants required a similar amount of time to complete data transformation in VR and on a desktop. Meantime, VR demonstrated the potential to facilitate strategic thinking and support provenance better. Subjectively, participants found the WIMP user interface on a desktop most familiar, and using VR was more physically demanding. On the positive side, VR was perceived as more engaging, and participants overall preferred the gesture-based experience in VR. **The contributions of this paper are twofold**: *first*, the designs of gesture-based interactions for essential data transformation operations on desktop and in VR; *and second*, a user study systematically investigating the effect of interaction methods (WIMP vs. gesture) and computing environments (desktop vs. VR) on performing essential data transformation operations.

## 4.2 Embedded and Embodied Gesture Design

Our study is intended to investigate the opportunities in using novel interaction methods (i.e., embedded and embodied Gesture) and emerging computing environments (i.e., VR) to

better support data transformation. We first reviewed the literature to identify the necessary operations and then designed gestures for both Desktop and VR.

### 4.2.1 Selecting Data Transformation Operations

Kasica et al. [87] summarized 21 fine-grained data transformation operations across five categories (i.e., create, delete, transform, separate, and combine) on three targets (tables, columns, and rows), see Table 4.1. As the first attempt to compare data transformation experience on desktop and in VR, we focus on basic operations that are commonly used by non-technical data workers without the need for programming. To this end, we excluded operations that require programming-like input, including *create*, *transform*, *separate*, and *combine* operations on rows and columns. For example, one typical *combine columns* operation can be inputting a formula to calculate the weighted average of selected columns. One exception was the *summarize rows* operation, as it does not require inputting a formula.

In summary, we support 12 operations, including all nine table, one-column, and two-row operations. See Table 4.1.

### 4.2.2 Designing Gestures

After analyzing the selected operations, we found that some operations have differences at the semantic level but imply the same interaction analogy. Specifically, Kasica et al. described *extend*, *supplement*, and *match* as operations to combine two data tables, with their difference being row-wise vs. column-wise combination or inner-join vs. outer-join [87]. All three operations suggest an interaction on two tables that results in one table. Thereby, we found one gesture (i.e., *merge*, see Fig. 4.1) can meet the semantic requirements of all three operations. The same applies to *subset* and *decompose*, and we used a combination of *filter+extract* gestures for them. Deleting tables, rows, and columns shares a similar gesture as the metaphor of throwing things away but differs in the target selection.

We iterate the gesture designs among the team members. The design objective is to ensure the gestures can intuitively reflect their semantic meanings of data transformation and that no conflicts exist between different gestures. Some initial gesture designs were inspired by the teaching materials of an undergraduate data science course taught by two co-authors, where

Table 4.1: A summary of our supported data transformation operations and their matching gestures.

| Operation | | Gesture |
|---|---|---|
| **Create** | create **tables** | ✘ |
| | create **columns** | ✘ |
| | create **rows** | ✘ |
| **Delete** | delete **tables** | delete tables |
| | delete **columns** | delete columns |
| | delete **rows** | delete rows |
| **Transform** | rearrange **tables** | sort |
| | reshape **tables** | reshape |
| | transform **columns** | ✘ |
| | transform **rows** | ✘ |
| **Separate** | subset **tables** | filter + extract |
| | decompose **tables** | filter + extract |
| | split **tables** | extract |
| | separate **columns** | ✘ |
| | separate **rows** | ✘ |
| **Combine** | extend **tables** | merge |
| | supplement **tables** | merge |
| | match **tables** | merge |
| | summarize **rows** | group / ungroup |
| | combine **columns** | ✘ |
| | interpolate **rows** | ✘ |

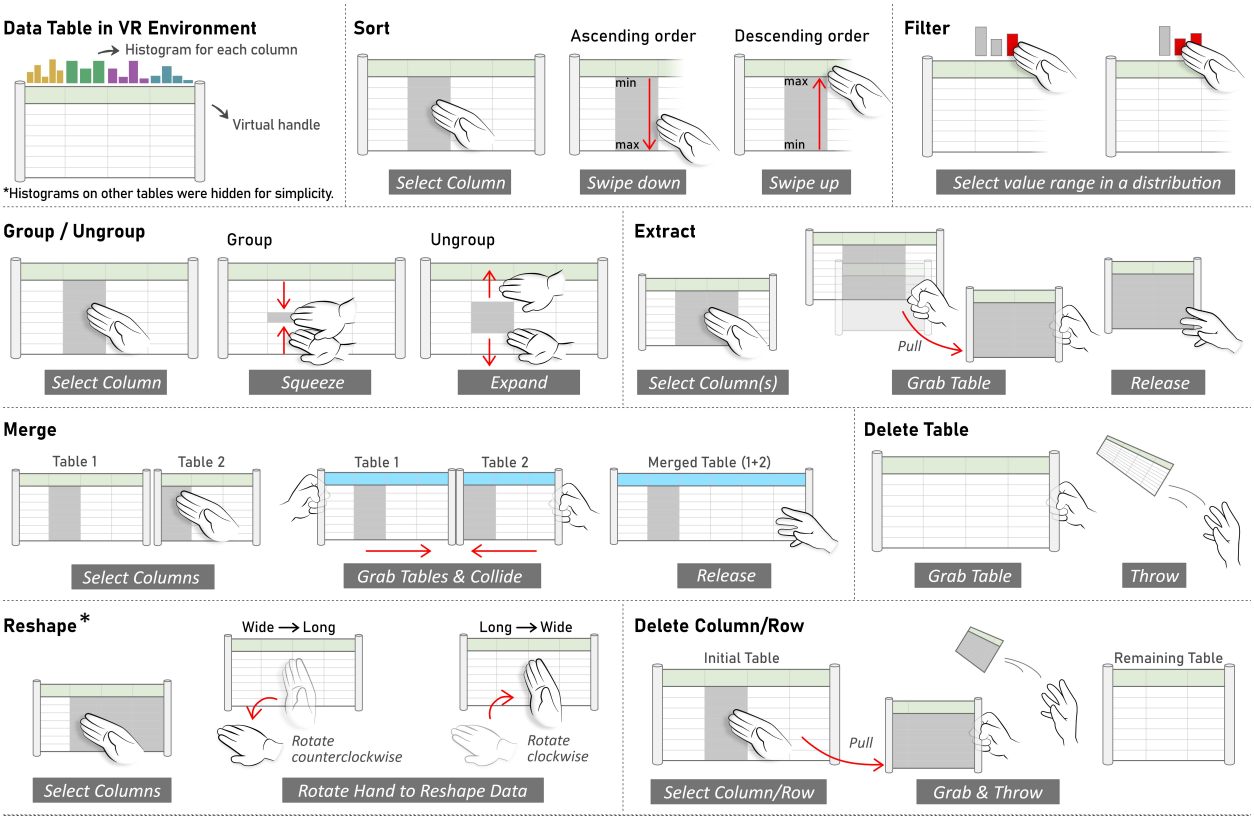



Figure 4.2: VR data table and gestures for data transformation tasks in the VR+Gesture condition. VR controllers, represented as hand models in the VR prototype and in the figure above, are used to perform these operations. The operation that was excluded from the study is marked with *.

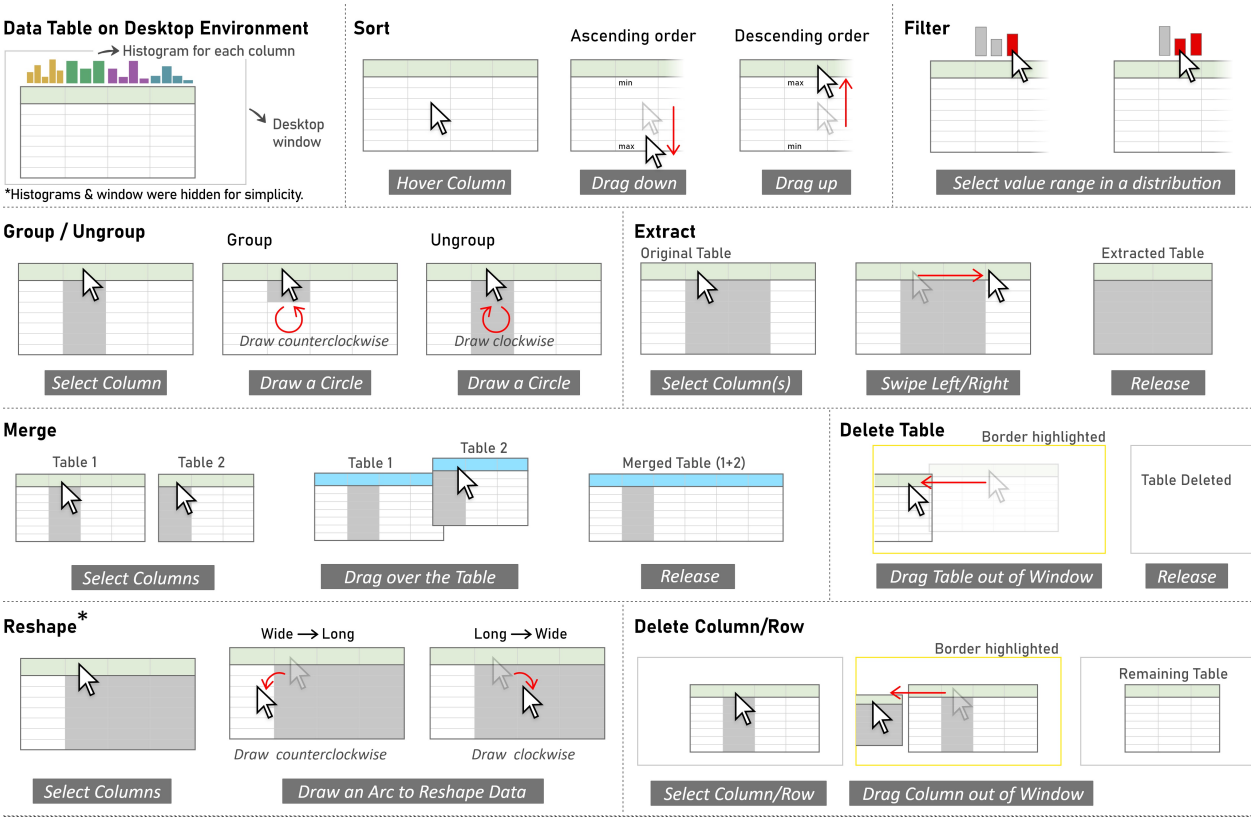



Figure 4.3: Desktop data table and gestures for data transformation tasks in the Desktop+Gesture condition. The operation that was excluded from the study is marked with *.

they frequently used gestures as metaphors for data transformation operations. Specifically, within a data table, horizontal movements were naturally linked to column operations, while vertical movements were considered row operations. Meanwhile, operations involving multiple data tables were intrinsically demonstrated as two-handed gestures. This initial design covered a good range of operations summarized by Kasica et al. [87]. We further introduced more gestures to increase the coverage of data transformation operations, Table 4.1. In summary, we have designed the following gestures:

- **Extract**: after selecting the target row(s) or column(s), *pull* them out from the original data table to create a new table with the selected content. The original table will be kept, and a new table will be created.

- **Merge**: *move* one table to *collide* with another table and *release* to combine two tables into one. If the key columns [70] are selected and match the criteria, an operation similar to *JOIN* in SQL will be performed. If no key columns are selected, and two tables share the same structure, an operation similar to *UNION* in SQL will be performed. Otherwise, the two tables cannot be combined. After merging, the original tables will be kept, and a new merged table will be created.

- **Filter**: for each column, a histogram is created to show its distribution. *Brush* the histograms to select the range of values to keep. The original table will be updated.

- **Sort**: *swipe* at a column from top to bottom or bottom to top to rearrange data in ascending or descending order. The original table will be updated.

- **Group/Ungroup**: after selecting the target column(s), *squeeze* to aggregate the values, while *expand* to restore the aggregated values to their original values. The original table will be updated.

- **Reshape**: after selecting the target column(s), *rotate clockwise* to transform LONG data shape to WIDE shape, while *rotate counterclockwise* to transform WIDE data shape to LONG shape. For LONG to WIDE, the values in target column(s) will be grouped into key-value sets, while for WIDE to LONG, the values in target column(s) will be categorized. The original table will be updated.

- **Delete**: after selecting target row(s), column(s) or table(s), *throw* them away to remove the selected content. The original table will be replaced.

Our gesture design on Desktop shares some similarities with the GestureDB system [27, 29]. We further adapted and extended those gestures into embodied interactions in VR. Most gestures require only one input device (i.e., for *extract*, *merge*, *filter*, *sort*, *reshape*, and *delete*). Those gestures are almost identical in interaction behaviors on Desktop and VR (i.e., consist of actions like click, drag, and drop). In VR, the ability to use two input devices (i.e., left and right hand-held controllers, which are visually represented as hands in our prototype) provides an alternative way to *merge* data tables: people can manipulate two data tables simultaneously by grabbing one in each hand and moving them close to *merge* them. The *group/ungroup* gestures also leverage the two input devices in VR to *squeeze* and *expand*, while we use the *draw a circle* counterclockwise and clockwise to imitate the same semantic meaning on the Desktop due to only one input device is available.

The designed gestures for VR are illustrated in Fig. 4.2, and the desktop gestures are presented in Fig. 4.3. We conducted a pilot study with three computer science graduate students who have data science experience to verify the usability of our designed gestures. Throughout this pilot, we confirmed the feasibility of our chosen gestures to complete data transformation tasks. The pilot study revealed no major operational issues and confirmed the intuitiveness of our gestures.

## 4.3 User Study

This study involves two primary experimental factors: the computing environment (or Environment, i.e., Desktop vs. VR) and the interaction method (or Interaction, i.e., WIMP vs. Gesture), see Fig. 4.4.

### 4.3.1 Study Conditions

To systematically investigate the two primary experimental factors, we included four conditions that cover all their interactions (Fig. 4.4), namely, Desktop+WIMP, Desktop+Gesture, VR+WIMP, and VR+Gesture (Fig. 4.1). The conditions are also demonstrated in the supplemental video.

**Desktop Conditions**: On the Desktop, we provide an *infinite canvas* as the primary working space. The infinite canvas is a *zoomable* and *pannable* canvas with no boundary

where the user can place and move digital content (data tables, in our case). It provides extra freedom to content organization and overcomes the size limitation of a physical screen. Various commercial tools (e.g., Miro [43], Google Jamboard [88], Microsoft Whiteboard [89], and SAGE [90]) use it as their working space, and there are also a series of attempts of using it in data science [90, 91, 92, 93]. Following their success and design, we allow the user to zoom in and out of the workspace by scrolling the mouse scroll wheel. The same interaction has been implemented in many widely used Zoomable User Interfaces (ZUI), like Google Maps. The user can also move data tables to any desired location using drag&drop. A mouse is the input device for the two Desktop conditions. In *Desktop+WIMP*, the user clicks buttons to trigger operations (Fig. 4.1(a)). We provide one button for each operation and place all buttons on a panel that is fixed on the right side of the screen. It is visible to the user all the time. In *Desktop+Gesture*, the user uses our implemented gestures (Fig. 4.3) to perform operations (Fig. 4.1(b)).

**VR Conditions**: In VR, we allow the user to physically move in the space and freely place and move data tables to any location around them. In *VR+WIMP*, operation buttons were placed on a panel and interacted in the same way as in Desktop+WIMP. Due to the different display spaces between Desktop and VR, it is unclear where to place this panel. To make the panel placement in VR as close as the Desktop+WIMP condition, we initially placed it using a head-reference approach [94], i.e., the panel will move as the user rotate their head, always visible to the user. However, our preliminary test indicates that such a design is distracting and annoying. We then changed the design to attach the panel to a left-hand-held controller according to [6], where the user can easily access or hide it with arm movements. The latter design was clearly preferred by the users we tested with, and was used in the user study (Fig. 4.1(c)). We also noticed participants struggled to select rows and columns precisely in our pilot study. Participants' comments revealed the need for a real-time visual indicator for selections. Thus, we rendered a "red dot" to indicate the pointer position on the data table. This mitigated the difficulties in selecting rows and columns based on another round of pilot tests. In *VR+Gesture*, the user uses our implemented gestures (Fig. 4.2) to perform operations (Fig. 4.1(d)).

**Summary**: WIMP and Gesture differ in the way they trigger the operations. Additionally, performing operations in WIMP requires the user to move the cursor or pointer back and forth between the data tables and menu panel, which is likely to introduce a context-switching cost, while the gestures are directly operated on the data tables. Desktop and VR both have

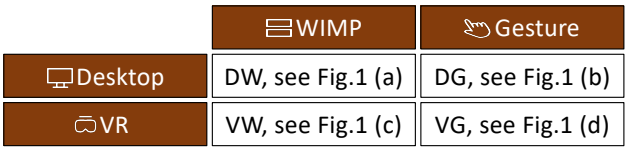



Figure 4.4: Our study compares two primary factors, leading to four conditions.

an "infinite" display space and let the user reposition the table at any location. Regarding the navigation method, the Desktop provides pan&zoom, while VR enables physical navigation.

### 4.3.2 Participants

We recruited 20 participants (Male=16, Female=4; Age from 18 to 35) from the university mailing list after screening for their data transformation experiences with a five-question quiz. 20 out of 25 respondents answered at least four questions correctly and were invited to participate in the study. Nine participants indicated they use VR regularly on a weekly basis, another nine only used VR occasionally, and the rest two had no VR experience. All participants had normal or corrected-to-normal vision. We provided a $20 Amazon Gift Card as compensation for each participant.

### 4.3.3 Experimental Setup

For VR conditions, we used a Meta Quest 2 virtual reality headset with 1920×1832 resolution per eye and a 90 Hz refresh rate. For Desktop conditions, we used a 27" monitor with a 2560 × 1440 resolution and 75 Hz refresh rate, which is a standard office setup. Both conditions use a PC with an Intel i7-11800H 2.30 GHz processor and NVIDIA GeForce RTX 3070 graphics card. We used the Air Link feature from Meta, which uses the PC for computation and the headset for rendering. Air Link enables a wireless experience while still leveraging the stronger computing power from the PC. Meanwhile, participants could move around more confidently without worrying about being tripped by cables. The study took place in the space of 3.5 x 3.5 meters ($12.25m^2$), and we let participants freely walk around the given area in VR conditions. The participants were asked to place themselves in the center of the actual space at the beginning of every VR condition. In Desktop conditions, participants sat on a comfortable office chair with the monitor placed in front of them on an office desk.

On the Desktop, every initial data table, including the target data table, was the same size as $530 \times 400$ pixels. The initial tables form a grid layout to maximize the use of display space, and the target table was placed in the middle for participants to reference and remember easily. In VR, five initial data tables, each with the size of $1.15 \times 0.65$ meters, were placed 1.65 meters in front of the participant's initial position in a semi-circular curved layout, which was identified as an effective space use strategy in VR for multi-window applications [33, 34], which allows all data tables to be placed at the same distance within participant's reach. The target table in VR was placed 35 cm higher than the initial table for the same purpose as in the Desktop conditions, i.e., to be easily distinguishable from other tables. The initial data tables and the target data table cannot be deleted. This is to avoid accidentally deleting those data tables and being unable to complete the task.

### 4.3.4 Task and Data

We asked our participants to *perform data transformations with five given data tables to produce a table in the target format*. Participants could move and resize all the given data tables and the target data table. To decide the number of given data tables, we piloted three different options (i.e., three, five, and eight). We found the task was too obvious with three tables and too difficult with eight tables, so we decided to use five tables for the study.

After training, the participants were asked to use data transformation operations to complete the task with each condition. Initially, we included all operations from Sec. 4.2.2. However, in our pilot tests, we found participants had a hard time conceptually understanding and applying the *reshape* operation, resulting in an unexpectedly long completion time for each trial (>30 minutes). This was aligned with some previous works [70, 87, 95], pointing out the *reshape* operation can be too complicated for novice users. Thus, we decided to remove the *reshape* operation from the task to target non-technical data workers and control the study duration. We further conducted another test without using *reshape*. Participants could complete the task in a reasonable amount of time (around 15 minutes per trial) without struggling. To ensure the difficulty of each trial was similar, all trials required a minimum of twelve operations. The sequence of the required minimum operations in each trial was different to reduce the learning effect.

We used tabular data sets collected online for training and study tasks. To eliminate the effect of participants' previous experience, we explicitly told them the data was not reflective

of real-world information. We also controlled the data size of initial data tables (row count for each: 30, total column count: ∼20) and target table (row count: 10, column count: ∼6). We have included all our study stimuli in the supplementary material.

### 4.3.5 Design and Procedures

The conducted user study followed a full-factorial within-subjects design. We used a Latin square (4 groups) to balance the study conditions. Each participant completed four study trials, i.e., one for each condition. The user study lasted two hours on average. The participants were first welcomed and reviewed to sign a consent form. Participants were then instructed about the purpose and steps of the study. They will then complete the following components of the study:

**Adjustment**: We asked participants to adjust the Quest 2 headset (e.g., the IPD) to a comfortable setting for the VR conditions. Similarly, for the Desktop conditions, participants were instructed to adjust the chair height to their preference before starting the tasks. We confirmed that all participants could see the sample text clearly in all conditions before proceeding.

**Training**: We first introduce the data transformation terms, considering people might use different terminologies for the same data transformation. We then introduced the computing environment (i.e., Desktop or VR) when a participant first encountered it. Sufficient time was provided for them to get familiar with the hardware until the participant asked to continue (usually around five minutes). For each study condition, when it first appeared to the participant, we first asked them to watch a video demonstrating each operation in that study condition. We confirmed that the participant fully understood how to perform each operation before moving to the next one. After that, we asked participants to perform the same task as in the user study but with only three initial data tables and one target data table. In this phase, we encouraged participants to ask questions about interactions and study tasks. All participants completed the training by finishing the task and confirmed familiarity with the study conditions (the training task took around five to seven minutes).

**Study Task**: The study task with each study condition started after participants completed the training session for that condition. Before we started the study, we ensured participants were well-informed by providing sufficient context. This included a brief overview of the

datasets and the high-level semantic meaning of the target data table. Participants had no time limit for task completion, but we instructed participants to complete the task as accurately and as fast as they could. For the VR environment, we repositioned participants to the room's center and let them face the same direction before each study task. All participants were able to complete the study task.

**Questionnaires**. *Post-condition questionnaires:* after completing the study task with each condition, participants were first asked to recall their performed operations in sequence. They were informed about this question at the beginning of the user study. They then filled out a Likert-scale survey adapted from SUS and NASA TLX to rate their subjective experience and provide qualitative feedback about the pros and cons of that condition. *Post-study questionnaires:* after completing all study tasks and post-condition questionnaires, participants were asked to rank all study conditions based on their overall experience. We asked them to provide demographic information at the end.

### 4.3.6 Measures

We collected quantitative data and interaction records for each study condition to capture their task performance and sense-making process. Specifically, we used the following measures. **Error score**: we compared the difference between the target table and the participant's result table by rows and columns. Each difference contributed to one error score. The order of rows was considered (as *sorting* operation was included in the task), while the column order did not affect the error score. **Time**: we measured the time from the initial data tables that were first rendered to the participant's task completion. **Number of operations**: we recorded the total number of operations performed by participants to complete the task. **Recall score**: we calculated the *Levenshtein distance* between the participant's actual performed operations sequence and recalled operations sequence that were collected in the questionnaire. A lower value means a closer match and suggests participants can remember their action history more accurately. **Number of performed delete operations**: we recorded the total number of performed table deleting operations in each study trial. **Number of data tables left:** we documented the number of data tables when the participant completed each study trial.

We also collected subjective ratings on a seven-point Likert scale for **mental demand**, **physical demand**, **learnability**, **engagement**, and **usability**. Lower mental and physi-

cal demands were considered positive, while higher learnability, engagement, and usability were treated as beneficial. Participants also **ranked** their overall experience. **Qualitative feedback** about each condition's pros and cons were collected from participants. Two authors derived a set of codes from the responses of the first five participants and applied the codes to the remaining responses.

### 4.3.7 Hypotheses

We developed our hypotheses based on previous empirical results and our analysis of study conditions, see Sec. 4.3.1.

**Error score**. We did not expect any difference in the error score as all required operations were provided consistently across all conditions. We believed that participants could complete the study task for all conditions successfully.

**Time**. We expected Desktop to outperform VR ($H_{time-env}$) based on previous studies, which found desktop interactions faster than VR interactions due to less required movement [69, 84, 96, 97]. Meanwhile, we anticipated Gesture to be faster than WIMP ($H_{time-interaction}$) considering better completion time of embedded/embodied interaction over WIMP found in earlier research [79, 80].

**Number of operations**. Our tasks require a sense-making process of foraging and structuring information to solve the problem. Under such a context, we considered VR requires a fewer number of operations than Desktop ($H_{ops-env}$) based on the previous investigation of sense-making in immersive space [49, 82]. We also expected Gesture requires a fewer number of operations than WIMP ($H_{ops-interaction}$). With a lower context-switching cost, Gesture would have fewer disruptions from navigation [98] and require less "mental map" rebuilding for the users [99, 100].

**Recall score**. We expected participants to have a better recall performance in VR than Desktop ($H_{recall-env}$), as VR with a 3D spatial environment was found to be more effective than Desktop for memorizing and retrieving information [101]. Meanwhile, we foresaw Gesture outperforms WIMP ($H_{recall-interaction}$) since performing body motions with the Gesture has a positive effect on memorability [102].

**Number of performed delete operations** and **data tables left**. We predicted a fewer number of delete operations ($H_{del-env}$) and a larger number of data tables left ($H_{left-env}$)

in VR than in Desktop. We argue that the larger display space in VR allows participants to keep more intermediate results and reduce the need to delete them. We also anticipated Gesture requires a fewer number of delete operations ($H_{del-interaction}$) and has a larger number of data tables left ($H_{left-interaction}$) than WIMP. As discussed, Gesture has a lower context-switching cost than WIMP, which can reduce the content organization workload and increase the maximum number of data tables participants can handle.

## 4.4 Results

We present our statistical results regarding our hypotheses, outline participants' strategies for using the display space and summarize qualitative feedback for each condition. For dependent variables or their transformed values that met the normality assumption, we used *linear mixed modeling* to evaluate the effect of independent variables on the dependent variables [103]. Compared to repeated measure ANOVA, linear mixed modeling does not have the constraint of sphericity [104, Ch. 13]. We modeled all independent variables (Environment and Interaction), and their interactions as fixed effects. A within-subject design with random intercepts was used for all models. We evaluated the significance of the inclusion of an independent variable or interaction terms using a log-likelihood ratio. We then performed Tukey's HSD posthoc tests for pairwise comparisons using the least square means [105]. We used predicted vs. residual and Q—Q plots to graphically evaluate the homoscedasticity and normality of the Pearson residuals respectively. For other dependent variables that cannot meet the normality assumption, we used the *Friedman* test to evaluate the effect of the independent variable, as well as a Wilcoxon-Nemenyi-McDonald-Thompson test for pairwise comparisons. Significance values are reported for $p < .05(*)$, $p < .01(**)$, and $p < .001(***)$. We also report mean values, 95% confidence intervals (CI), as well as Cohen's d as an effect size indicator for significant comparisons.

### 4.4.1 Quantitative Results

Results are illustrated in Fig. 4.5, Fig. 4.6, and Fig. 4.7. All statistical analyses and anonymized data were included in the supplementary material.

**Error score.** As expected, all participants could complete the study task correctly under

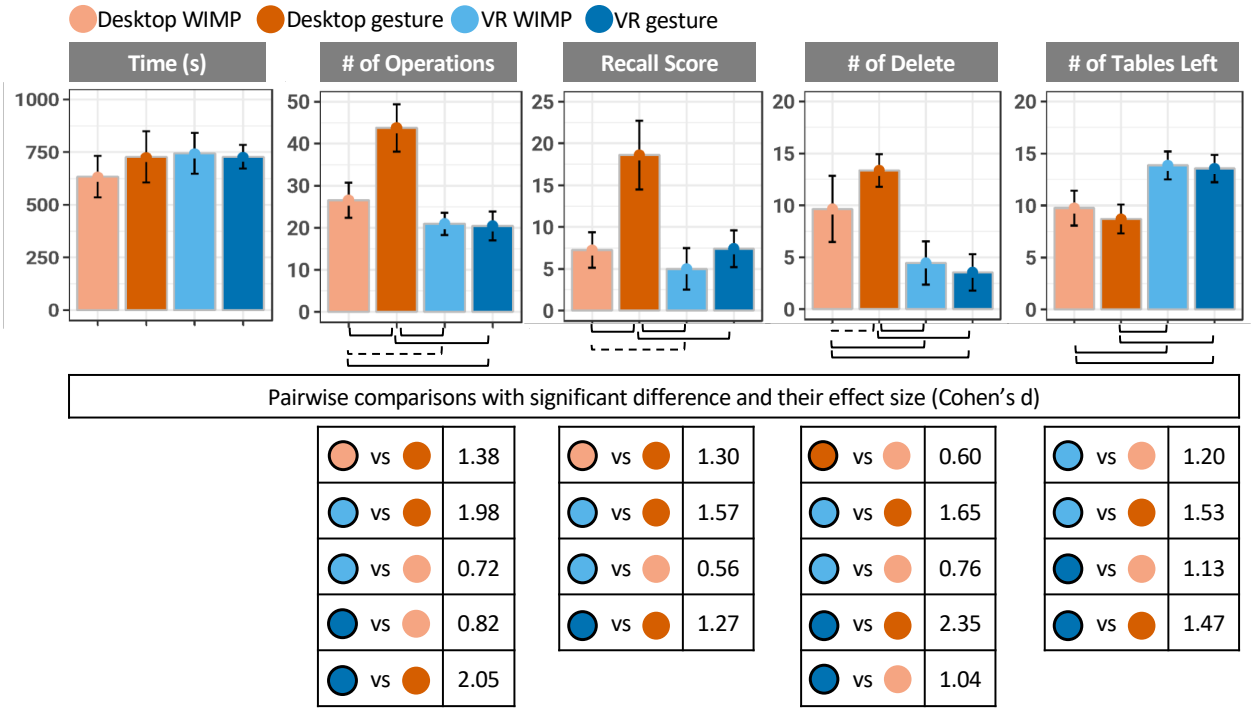



Figure 4.5: Measurement of time, the total number of operations, recall score, the number of delete operations, and the number of tables left by task. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below show the effect sizes for pairwise comparison. Circles with black borders indicate the winning conditions.

all conditions.

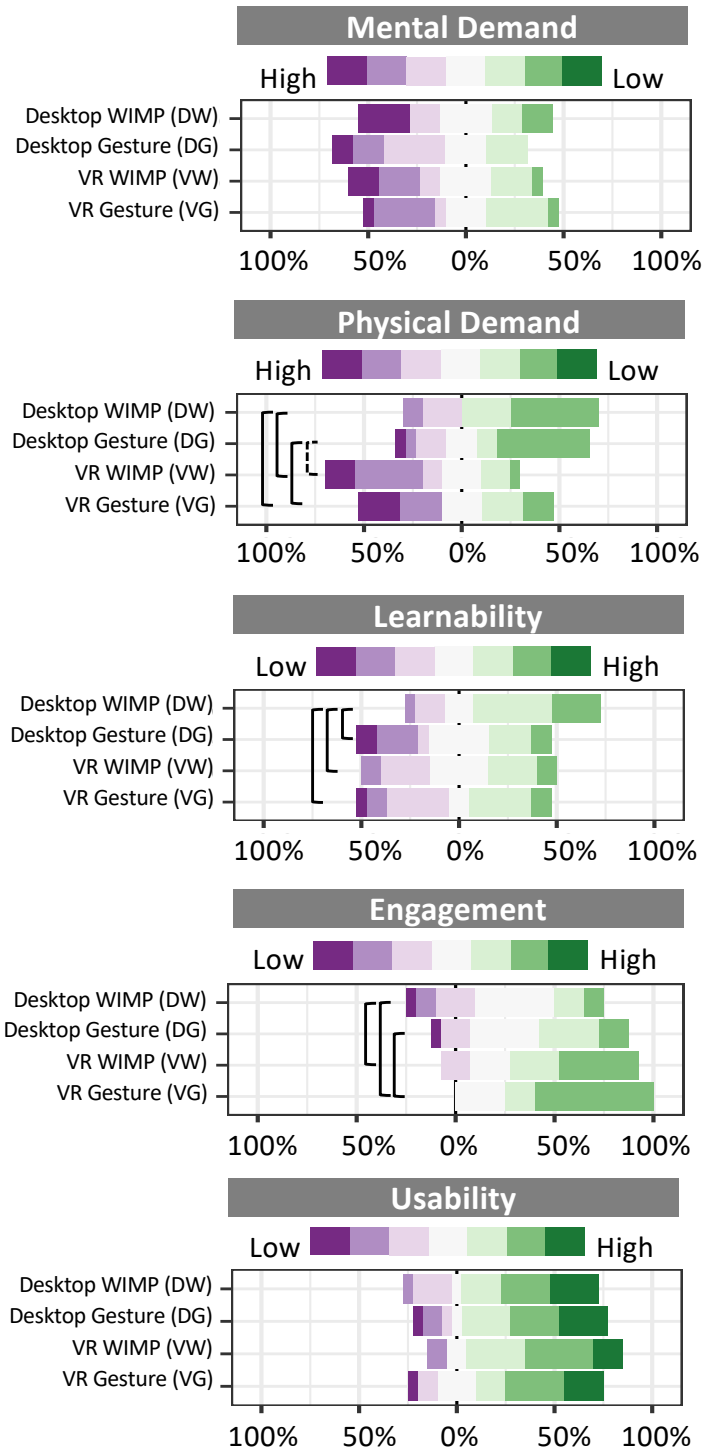
**Time.** Surprisingly, we found Environment ($p = 0.14$), Interaction ($p = 0.51$) and their interaction ($p = 0.42$) did not have a significant effect on time. All conditions took similar amount of time: Desktop+WIMP (634s, CI=73s), Desktop+Gesture (727s, CI=134s), VR+WIMP (744s, CI=116s), and VR+Gesture (728s, CI=96s). Desktop+WIMP tended to be slightly faster but without statistical significance. Thus, we reject $H_{time-env}$ and $H_{time-interaction}$.

**Number of operations.** We found significant effects of Environment ($***$), Interaction ($***$) and their interaction ($***$) on the total number of performed operations. VR conditions (WIMP with 21.0, CI=2.90 and Gesture with 20.5, CI=2.54) required less number of operations to complete the study task than Desktop conditions (WIMP with 26.6, CI=4.22 and Gesture with 43.8, CI=7.06). All comparisons were statistically significant ($*$) except for the comparison between VR+WIMP and Desktop+WIMP ($p = 0.057$). On Desktop, Gesture also required more operations than WIMP ($***$). In summary, we accept $H_{ops-env}$, and reject $H_{ops-interaction}$.

**Recall score.** We found significant effects of Environment ($***$), Interaction ($***$) on the recall score, with a marginally significant effect from their interaction ($p = 0.081$). Condition-wise, participants can remember their action history better in VR+WIMP (5.0, CI=1.83), VR+Gesture (7.4, CI=2.20), and Desktop+WIMP (7.3, CI=1.94) than Desktop+Gesture (18.6, CI=5.42). VR+WIMP was also marginally more memorable than Desktop+WIMP ($p = 0.078$). For both the WIMP and Gesture, VR could better support the recall process than a Desktop. Dekstop+WIMP was also found more memorable than Desktop+Gesture ($***$). In conclusion, we accept $H_{recall-env}$, and reject $H_{recall-interaction}$.

**Number of performed delete operations** and **number of data tables left**. For the number of performed deleting operations and the number of left tables, there was a significant effect from Environment (all $***$). Interaction only had a significant effect on the number of performed deleting operations ($*$). Participants deleted fewer tables and kept more data tables in VR than in Desktop (all $***$). In summary, along with accepting $H_{del-env}$ and $H_{left-env}$, we reject $H_{del-interaction}$ and $H_{left-interaction}$.

**Ratings.** We found a significant effect of the study condition on *physical demand* ($***$), *learnability* ($**$), and *engagement* ($***$). Participants found VR conditions (WIMP with 4.0, CI=0.71 and Gesture with 3.7, CI=0.92) more physically demanding than Desktop con-




| Comparisons with significant difference | effect size (Cohen'sd) |
|---|---|
| **DW** vs. VW | 1.16 |
| **DW** vs. VG | 0.83 |
| **DG** vs. VW | 0.82 |
| **DG** vs. VG | 0.57 |
| **DW** vs. DG | 0.81 |
| **DW** vs. VW | 0.55 |
| **DW** vs. VG | 0.70 |
| **VW** vs. DW | 0.92 |
| **VG** vs. DW | 1.34 |
| **VG** vs. DG | 0.95 |

Figure 4.6: Subjective ratings on mental demand, physical demand, learnability, engagement, and usability by task. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$.

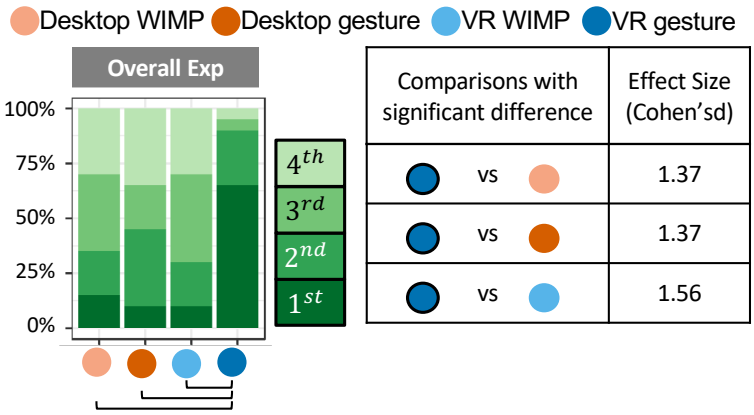



Figure 4.7: User ranking of overall user experience for each condition. Solid lines indicate significant differences with $p < 0.05$.

ditions (WIMP with 2.25, CI=0.69 and Gesture with 2.6, CI=0.88). Participants considered Desktop+WIMP (4.7, CI=0.55) most easy to learn, with Desktop+Gesture (3.45, CI=0.81), VR+WIMP (4.0, CI=0.55), and VR+Gesture (3.7, CI=0.76). VR+Gesture (6.4, CI=0.41) was found more engaging to use than Desktop conditions (WIMP with 4.7, CI=0.73 and Gesture with 5.3, CI=0.64).

**Ranking.** Participants ranked the VR+Gesture as providing the best overall experience, with 65% ranked it as first place, and 25% ranked it as second place (i.e., 90% in total ranked VR+Gesture as the first or second place).

### 4.4.2 Layout Strategies

To better understand how participants used the display space, we grouped the final layout of each trial. We found participants had different strategies in Desktop and VR, but used a similar layout between Gesture and WIMP. All final layouts are included in the supplementary material.

On Desktop, we identified four different layout strategies (Fig. 4.8): **Grid** (five). Participants placed their data tables in a regular layout, closely forming a grid shape. **Piling** (one). The participant created a few piles of data tables. **Grid+Piling** (five). The participants created a regular layout with some piles of data tables. **No obvious pattern** (nine). Roughly half of the participants did not demonstrate a clear layout pattern and created an "organic" layout.

In VR, 19 out of 20 participants almost did not move the five initial tables or the target table. Participants seemed to treat these given tables in as *strong anchors* and were reluctant to manipulate them. This observation might reflect participants' intention to keep data provenance. Thus, VR might increase the awareness of provenance and allow the track of provenance to be more manageable. Regarding the final layouts, we found three different strategies (Fig. 4.9). 17 participants performed data transformation behind themselves: **Behind-cluster** (16). Participants created a few clusters at the back of their initial orientation. **Behind-piling** (one). Participants piled data tables in one cluster and formed a roughly vertical line at the back of their initial orientation. **Front** (three). Participants used the space in front of their initial orientation, and to avoid occlusions, they had to delete data tables more frequently. In all strategies, we observed that participants preferred to stay in the center and place data tables close to them to reduce physical movements.

Due to limited data points in some strategies, we could not identify significant performance differences between different strategies, except that the *Front* strategy required more *deletion and total operations* and had fewer *tables left* than other strategies utilizing the entire 360° circular space in VR.

### 4.4.3 Qualitative Feedback

We performed qualitative coding to extract common themes from user feedback on each condition. For each condition, we listed the top three mentioned codes and those mentioned more than five times by the participants (frequency shown in parenthesis). We further highlighted the top codes with other frequently associated codes. Finally, we summarized the overall insights across all conditions. The complete coding results can be found in the supplemental materials.

**Desktop+WIMP** was considered *straightforward* (7), and *familiar* (5). The downsides were *limited space* (11), *hard to interact* (6), and button interaction were *not intuitive* (5). Specifically, limited space was the primary concern, as shown by its association with several codes, including hard-to-interact (3) and the constant shift in focus from the working window to the buttons created task disruptions when executing operations (2).

**Desktop+Gesture** was considered *intuitive (15)*, *better than button* (8), and *easy to use* (8). Because of the intuitive feeling, it was considered better than buttons and easy to

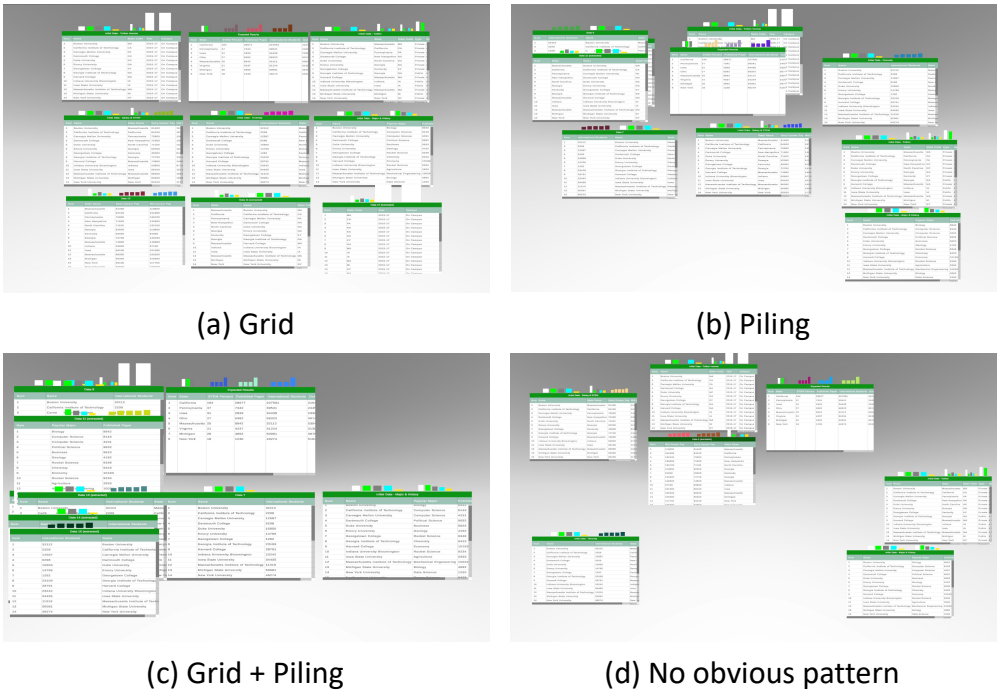
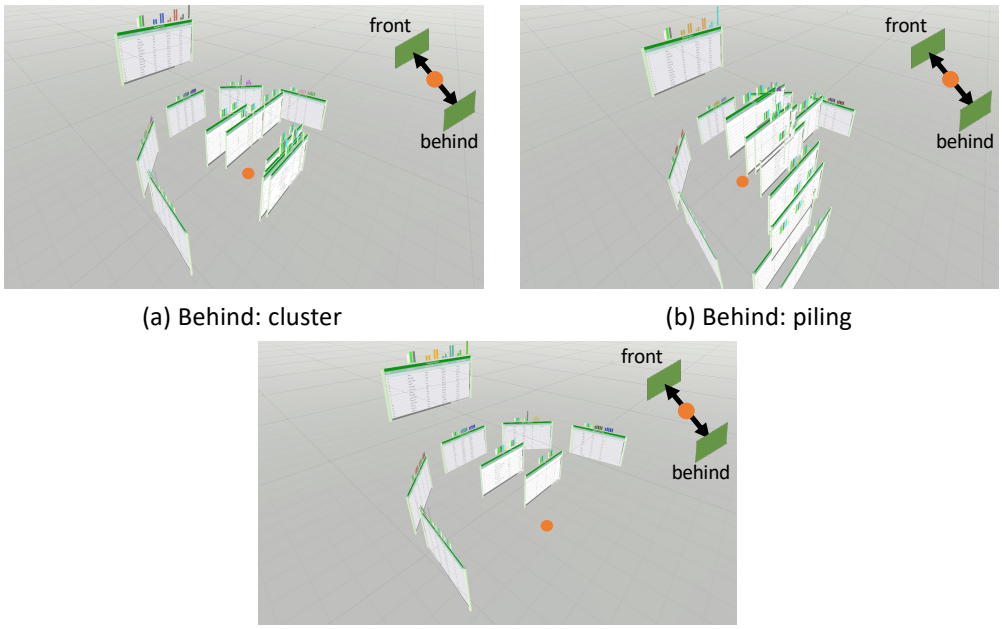



Figure 4.8: Four layout strategies used by our participants on Desktop.

use by five users, good for merging by four users, and good for sorting by two users. The primary issues included *limited space* (9), *hard to interact* (8), *discoverability issues* (6), and *functionality* (5). Similar to the Desktop+WIMP, the limited space was the predominant concern linked to other codes. This included instances where gestures were occasionally challenging to execute due to the limited space, which resulted in creating task disruptions (3), particularly when executing certain functions (3) that demanded more space, such as extraction tasks.

VR+WIMP was praised with *large space* (12), *better than desktop* (9), *grabbed&moved* navigation was *intuitive* (7), *easy to use* (6), and *flexible* (6). Specifically, the major benefit of the large space was associated with flexibility by five users, easy to use by two users, and good understanding by two users. Among comments on better than desktop, people referred to it as easy to use (5), easy to organize (2), and accessible (2). Conversely, the issues related to *functionality* (13). In addition, one participant pointed out that using a pointer to select two tables from a dropdown menu caused greater disruption when trying to execute merge operations compared to the Desktop+WIMP setup. The concerns arose regarding the constant need to hold buttons on the left hand, causing task disruptions (6), along with another reason similar to those encountered with the Desktop+WIMP. People




(a) Behind: cluster (b) Behind: piling

(c) Front

Figure 4.9: Three layout strategies used by our participants in VR. The red dot indicates the position of the participant.

had diverse opinions on the functionality, such as hard-to-select (3), heavy headset (2), and other technical issues like resolutions.

VR+Gesture was found to be *intuitive* (17), *better than button* (10), *easy to use* (7), *straightforward* (5), and *flexible* (5). The majority (17) found it intuitive and subsequently associated it with better than buttons (7), easy to use (6), and flexible (4). Three also cited more accessible, and the other three cited large spaces. Furthermore, people considered it better than buttons mainly because it is easy to use (4), straightforward (4), accessible (3), and promotes good understanding (2). Participants particularly spoke highly about gesture interactions and grab&move navigation. On the other hand, the major concern was *functionality* (12), mostly with resolution and technical issues (7), but no specific functionality issues were found to perform operations in VR+WIMP.

**Summary.** All conditions were considered *easy to use*. In Gesture conditions (Desktop+Gesture and VR+Gesture), the majority cited *intuitive* (15 and 17 times, respectively) and considered them *better than button* (8 and 10 times). VR conditions (VR+WIMP and VR+Gesture) were considered *flexible* (6 and 5 times) and *better than desktop* by several users (9 and 4 times). Interestingly, Desktop+WIMP and VR+Gesture each were cited

*straightforward* by a handful of users (7 and 5 times), indicating that users have expected that WIMP is natural for desktop and 3D gestures for VR environment.

On the other hand, Desktop conditions hinder interaction due to *limited space* (11 and 9 times) and *hard to interact* (6 and 8 times). With VR conditions, the majority have commented on *functionality* (13 and 12 times) due to the unfamiliarity with data transformation in VR, such as technical issues and feature suggestions. In VR+WIMP, people found it *hard to interact* and *select* (5 times), leading to creating *disturbed* (6 times).

## 4.5 Key Findings and Discussions

**Performing data transformation in VR and on a Desktop had similar time performance.** Previous studies produced mixed results in comparing VR and Desktop. In immersive analytics, for completion time, VR was found to be primarily beneficial for visualizing spatial data and 3D shape perception [3, 106], and to be slower than Desktop due to more required movements (see our *time* hypothesis in Sec. 4.3.7). Our tested task did not involve perceiving 3D or spatial visualization, so we expected Desktop to be faster than VR. Surprisingly, our four tested conditions had similar time performance. We believe the empirical results of VR being slower than Desktop in performing interactions still applied to our case, which is partially reflected by the fact that VR conditions were considered significantly more physically demanding than Desktop conditions. On the other hand, unlike the previously tested tasks, our tested task not only involved low-level interactions but also required participants to actively make sense of the data to come up with a sequence of interactions to complete the task. We could reasonably expect participants to put a significant amount of effort into thinking and planning strategies for a complicated task like ours. Based on this assumption and our results, we suggest that VR allows participants to complete the high-level sense-making components faster than Desktop, which supplements its extra time costs in performing low-level interactions. Below, we elaborate more on the high-level sense-making process from the *provenance* and *strategic thinking* perspectives.

**VR showed the potential to provide improved provenance over Desktop.** Provenance is about the lineage and processing history of data. It provides a detailed record of the origins of the data, how it has been processed or modified, and where and when it transformed over time [107]. The ability to track provenance can support many applications,

like data quality control, data auditing, and replication [108]. In our study, we used the *recall score*, *the number of performed delete operations*, and *the number of data tables left* as indicators of certain aspects of provenance. The *recall score* measures the ability to recall the operation history, reflecting when the data was transformed. The latter two metrics offer objective measures of the amount of kept information.

In addition to the previously confirmed memorability advantage in VR (see our provenance hypothesis in Sec. 4.3.7), we believe the large display space and embodied navigation in VR also helped participants keep track of provenance. *First*, participants had more space to place tables in VR, whereas on Desktop, they were more likely to delete tables to free display space to reduce clutter. Our results of fewer table deletions and more kept tables in VR than on Desktop are well aligned with provenance tracking ability. The data tables, kept persistently visible, provided a reliable reference for participants to confirm the success of their current operations. Moreover, they were a handy tool for participants to return to whenever they made mistakes. This was likely due to the large display space provided within the VR setup. Particularly, nine participants explicitly complained about the display space on the Desktop; for example, *"I have a very limited workspace (on the desktop), and cannot see all the tables at once, which really hurts my performance (P15)."* This limited space on the Desktop lets participants continually delete the data tables, which leads to a loss of opportunities to keep track of the processing history. *Second*, we consider physical navigation more efficient than virtual navigation. Previous research identified the benefits of using physical movements to navigate large displays over virtual navigation (i.e., zooming) [109, 110]. Our results partially re-confirmed their findings in VR. 12 participants' comments reconciled with our assumption, like, *"I have all data tables in front of me without zooming in & out, and I can focus on the task (P12)."* We found that the participants prefer physical navigation, as it offers a more intuitive and faster method for altering the perspective view of their workspace for accessing all kept information. One participant also specifically described the use of large display space to improve spatial memory and embodied navigation in VR: *"I like the point that I put the data table behind me so that I can come back if I make mistakes (P7)."* This feedback aligns well with the improved provenance in VR, which enhances data quality through auditing without manually documenting every detail of each step. However, provenance is still a relatively abstract concept, and our measurements also only captured certain aspects of it. More effort is needed to formally define and quantify provenance in data transformation.

**VR demonstrated preliminary evidence of promoting strategic thinking.** Participants needed to continuously develop the next steps in our tested task and evaluate their progress. We found VR required fewer operations to complete transformation tasks than Desktop, which points to the potential advantages of VR in supporting strategic planning. With the improved provenance, it is likely that VR users can better track the progress and take more efficient steps. Another potential reason is the flexible arrangement of VR tables that support easier visual comparison. We observed *all 20* participants in VR *grabbed&moved* their working table under the target table for comparison. Meanwhile, participants rarely performed a similar interaction on the Desktop. We believe such frequent comparisons enabled continuous progress evaluation and promoted strategic thinking in VR. We anticipate the embodied table management (i.e., the grabbed&moved) and large display space in VR provide a natural mechanism to support such an approach. In contrast, the need for repetitive zooming in/out on Desktop made participants reluctant to perform the same strategy. Additionally, participants also commented on their experiences along this line, for instance, *"I have many more places to put the data table (in VR). Organizing the table was way more manageable (P14)." "The interaction in VR was way better than the monitor version; the task became way more accessible, and organizing was easy (P3)."*

**WIMP tended to be more suitable for Desktop than Gesture.** Unlike previous studies [79, 80], we did not find positive effects on the collected measures of using Gesture over WIMP on a Desktop. We believe the task and gesture complexities could be the main reasons for our contradictory results. We tested a more complicated high-level task (average completion time was 10+ minutes per trial) than the previous low-level tasks (average completion time was around one minute per trial). Performing a single interaction using Gesture could outperform WIMP in our study, but the complexity of Gesture might introduce other overheads that decreased its performance significantly in our tested task. The subjective ratings partially confirmed our assumption: Desktop+Gesture was considered harder to learn than Desktop+WIMP. Participants had to remember more gestures (eight) than in the previous studies (three in [79] and five in [80]), which might introduce a high working memory and affect their performance, especially in a more complicated task. The fact that participants struggled with recalling their action history in Desktop+Gesture resonated with our conclusion, with some representative comments like: *"The interaction was confusing (in Desktop+Gesture). I think I would like[ly] have more errors than other conditions."*.

**No noticeable difference in time, efficiency, and provenance measures between**

**WIMP and Gesture in VR.** Similar to Desktop, the identified benefits of body motion [102] might also be affected by the task and gesture complexities in VR. On the other hand, we did not find any significant difference between VR+WIMP and VR+Gesture, indicating the overhead introduced by learning and remembering Gesture in VR could be negligible due to its intuitiveness. Participants ranked VR+Gesture with the best overall experience, and some commented on the benefits of using Gesture in VR explicitly, like *"Embodied interaction helps me a lot in understanding the data story (P2)"* and *"Using both hands was very helpful in performing the task (P4)."* More importantly, the embodied table management (i.e., the grabbed&moved) and physical navigation were provided in all VR conditions. Compared to interactions for triggering the operations, these two features might contribute a heavier weight in the final performance, making both VR conditions have similar performances. Furthermore, the perceived intuitiveness of the gestures and embodied interactions was reflected in the feedback we collected. Comparably, none of the participants explicitly mentioned Desktop+WIMP to be intuitive.

**Various layout strategies exist in both environments.** The "infinite" space in both the desktop and VR conditions allowed participants to freely lay out content in their workspaces. We found two distinct dimensions in their strategies: *space usage* and *view management methods*. For space usage, on Desktop, most participants only used space slightly larger than the initial setup (Fig. 4.8) with 6 to 9 data tables and adjusted the view by zooming. On the other hand, the majority of participants in VR utilized the entire 360° circular space around them to fit more data tables (12 to 15) (Fig. 4.9). In VR, previous studies observed using semi-circular layouts were more frequent [34] and beneficial over 360° layouts [33, 60] for performing low-level tasks (e.g., search and comparison). However, for high-level tasks, our observations aligned well with some other works, such as sensemaking [50] and visual exploration [111], where people preferred using the entire fully circular space. We anticipated that placing content within the field of view is beneficial for time-constrained low-level tasks, while fully utilizing the display space is essential for the larger amount of content generated in high-level tasks. In terms of view management methods, the layout on the Desktop was considerably more organized than in VR, showing that precise view placement is easier with a mouse than with a VR controller. However, user behaviors were similar across both Desktop and VR. Most participants intended to create occlusion-free clusters (e.g., a grid layout in Fig. 4.9-b), yet some participants created piled clusters (e.g., a piling layout in Fig. 4.9-a), which was also observed in a recent AR study [112]. We also noticed the use of space to record the operation history from some participants (e.g., moving older tables to the top),

which has been identified on large 2D displays [59].

## 4.6 Conclusion

In this paper, we presented our prototypes to enable embedded interactions on the Desktop and embodied interactions in VR for data transformation. We conducted a controlled user study to systematically evaluate the effect of the computing environments (Desktop vs. VR) and interaction methods (WIMP vs. Gesture). We found initial evidences showing the benefits of using VR for data transformation: VR had the potential to provide improved provenance over Desktop and demonstrated preliminary evidence of promoting strategic thinking. VR also had a similar time performance compared to Desktop. Additionally, participants found VR to be more engaging, and VR+Gesture provided the best overall experience. Considering the iterative nature of data science, we foresee strong initiatives to combine immersive data transformation and visualization to enable a more complete *Immersive Analytics* workflow, reducing the overhead of switching between different computing environments. On the other hand, we did not find a better performance of Gesture over WIMP. We still believe there is potential to improve Gestures, for example, by providing long-term training and real-time memory assistance. In summary, our results provide preliminary evidence that the large display space, spatial memory, and embodied navigation in VR are beneficial for high-level data transformation tasks.

# Chapter 5

# ICoN: Immersive Computational Notebook for Data Science

## 5.1 Introduction

Immersive Analytics (IA) is an emerging and promising field that aims to enhance data analysis processes through immersive technologies [3, 4, 17]. Despite its potential, there is a significant gap between the current IA ecosystem and the common practices in data science. IA often focuses on individual components of data science, such as data transformation or visualization, but does not support the iterative nature of data science workflows well [9]. This iterative process typically requires frequent switching between tools, which incurs high context-switching costs and disrupts the analytical flow.

Computational notebooks have become a mainstream tool in data science due to their ability to integrate multiple processes into one cohesive platform, supporting the iterative nature of data analysis [13]. Motivated by the success of computational notebooks, In et al. [16] developed and tested a basic adaptation of computational notebooks in immersive environments by arranging notebook cells around the analysts in space. Their findings highlighted some benefits of this approach; however, they also noted that the traditional WIMP (windows, icons, menus, pointer) paradigm negatively impacts the productivity of data science tasks in immersive environments. This signals the need for a new interaction paradigm for immersive computational notebooks.

Embodied interaction, which leverages physical movements to interact with digital content, offers an intuitive and effective interaction experience by enabling direct manipulation [83, 84]. Previous research has explored designing embodied interactions for performing data science tasks in immersive environments. For instance, In et al. [30] designed gestures for data transformation, Cordeil et al. [8] proposed assembling axes to build data

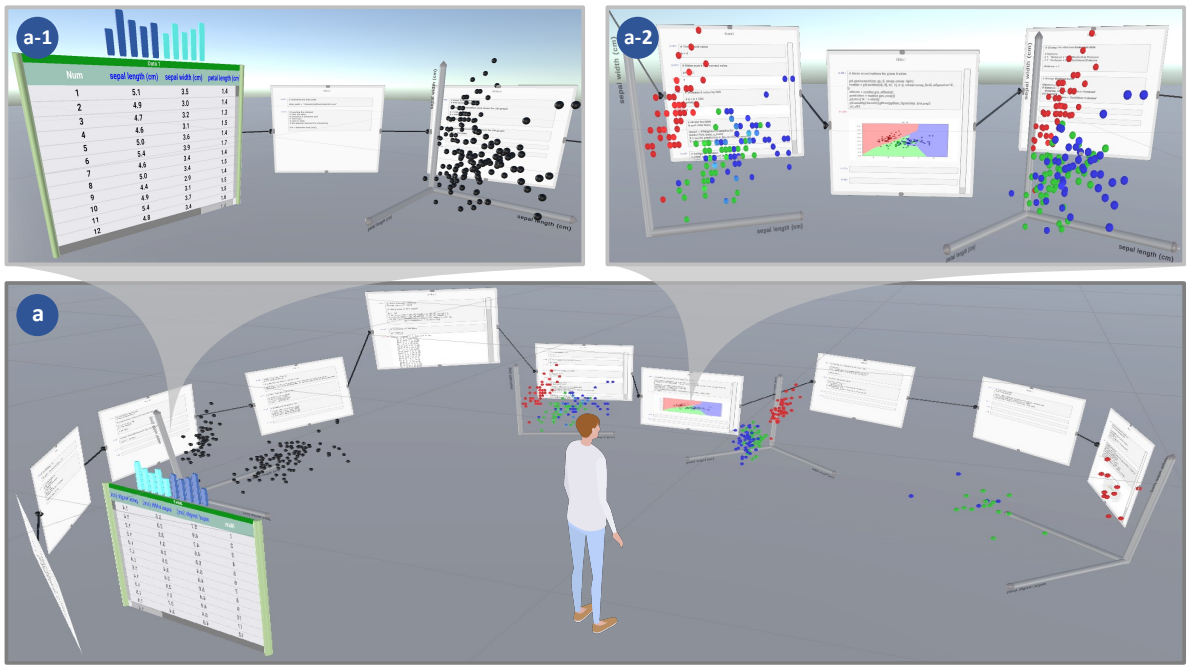



Figure 5.1: User performs data science tasks with an immersive computational notebook (ICoN). They can seamlessly transition between notebooks and embodied workspaces within a unified environment. Specifically, (a-1) a user can directly pull out a data table from the notebook, and create visualizations from the data table through embodied interactions. (a-2) A user can also pull out visualizations that are embedded in the notebook and manipulate them, for example, by grabbing an additional data dimension from the table and adding it to a 2D scatter plot as a new axis (left) to create a 3D scatter plot (right). After exploring data tables and visualizations, the user can put them back into the computational notebook to update the code.

visualizations, and Zhu et al. [113] explored combining multiple visualizations by grabbing and colliding them. While these interactions were found to be effective and engaging, integrating them into a unified space to support iterative data analysis workflows remains under-explored. Given the widespread adoption of computational notebooks in data analysis, integrating embodied interactions into immersive computational notebooks presents a promising approach to addressing the limitations of the traditional WIMP paradigm for immersive computational notebooks. However, this integration poses several challenges, such as how analysts can switch between different processes across different workspaces and what are the best practices for managing notebooks and embodied spaces.

To tackle these challenges, we explored how to integrate embodied interactions into immersive computational notebooks. We developed seamless transition techniques to "glue" different data analysis processes together with embodied interactions, focusing particularly on data transformation and visualization processes. Additionally, we introduced embodied interactions to allow analysts to exchange and update artifacts across notebooks (i.e., code) and embodied spaces (i.e., data tables and visualizations). We call our developed prototype system ICoN.

To provide empirical knowledge about the effectiveness and user experience of ICoN, we focused on investigating the impact of its two primary characteristics: immersion and unified workspace. Immersion, in this context, refers to the ability to perform spatial and embodied interactions within a large, immersive space. A unified workspace pertains to the capability of conducting various data analysis tasks—primarily data transformation and visualization in this project—in a single, cohesive display space, reducing the context-switching cost. To empirically assess the potential benefits of immersion, we compared our immersive systems to their desktop counterparts. To understand the advantages of a unified workspace, we compared it to separated workspaces. Therefore, we conducted a controlled study with four conditions covering all combinations between (Desktop vs. VR) and (Separated vs. Unified). We found that ICoN (VR+Unified) facilitated more intuitive and faster transitions and enhanced exploratory capabilities throughout the data science process. However, while the Unified workspace enabled effective transitions, participants expressed concerns about the limitations of the available space, particularly on the Desktop.

In summary, our main contributions are:

- We built a research prototype system that facilitates a hybrid data science workspace,

enabling seamless transitions between computational notebooks, embodied data transformation, and embodied data visualization workspaces.

- We conducted a controlled user study comparing computing environments (Desktop vs. VR) and workspace configurations (Separated vs. Unified) within computational notebook settings for data science tasks.

## 5.2 Design Rationale and Considerations

Our primary goal is to integrate two distinct user interfaces and interaction paradigms in immersive environments to enhance the data analysis process.

In immersive environments, adapting *computational notebooks* by spatially distributing cells around the analyst supports intuitive physical navigation, allowing analysts to move through the space and easily shift focus across various components of data analysis [16]. This physical navigation has been found to be more effective than virtual navigation methods such as mouse scrolling or panning [110]. Additionally, the linear structure of computational notebooks provides a familiar and predictable framework for analysts to follow the entire analysis process [22, 114]. However, computational notebooks are inherently programming platforms, requiring precise interactions like pointing to small targets (like menu items) and text input, which can significantly impair user experience and disrupt the perception of flow [80].

*Embodied interaction*, on the other hand, offers a promising alternative by enabling physical and direct manipulation of visual artifacts instead of traditional pointing and coding [30]. While embodied interactions have been successfully designed for individual data analysis tasks (e.g., data transformation and visualization authoring), transitioning between and connecting these tasks in an immersive embodied space is challenging. In desktop settings, although data files often serve as proxies to connect multiple data analysis tools, incorporating file management in immersive settings could introduce additional complexity and requires precise interactions, as previously discussed, difficult in these settings. Furthermore, previous studies have shown that having data artifacts, such as tables and charts, floating around the user can lead to disorientation in the analysis process and increased effort in managing layout and space usage [30].

Given the strengths and limitations of computational notebooks and embodied interaction,

we believe there is a significant opportunity to combine them into a unified workspace to complement each other. However, simply merging these two systems may not be effective, as the overhead of switching between them could outweigh the benefits. Therefore, we need to design interactions that address the identified issues in each system and allow analysts to seamlessly transition between them. To guide our design, we reviewed literature and empirical findings from previous studies. We identified that Csikszentmihalyi's flow theory [115] aligns well with our high-level design goal of increasing fluidity and the sense of flow in data analysis, providing fundamental theoretical guidance. We also found that Elmqvist et al.'s design principles of fluid interaction [116] narrow the scope of flow theory and offer more actionable guidelines. Specifically, fluid interaction principles suggest that interactions should 1) promote flow, 2) support direct manipulation, and 3) minimize the gulf of action. Following the design principles of fluid interaction, we propose the following design considerations for combining the two systems, focusing on providing a seamless transition experience.

**DC1: Provide low-effort transitions that promote flow.** Broadly speaking, we envision two types of transitions in the combined system: navigational and interactive. Navigation refers to interactions that change the viewpoint, allowing analysts to access different information. On the desktop, panning or scrolling are common interactions for navigational transitions. In the immersive environment, natural walking or rotating head is a standard and effective way to achieve navigational transitions [117]. Interactive transition is a unique type of transition in our setting, involving the change of data artifact representations, for example, converting a static visualization image rendered in the computational notebook into an interactive visualization in the immersive space. We will focus on designing and building low-effort for interactive transitions, as the navigational transitions in immersive environments have already been effective in data analysis.

**DC2: Enable embodied transitions that support direct manipulation.** Direct manipulation refers to interacting with digital objects like interacting with physical objects [77, 118]. This approach allows the physical movement and the interacted object to exist in the same physical space, reducing spatial perception misalignment [6]. In immersive environments, one of the most common and well-recognized direct manipulations is grabbing and moving a digital object. We want to leverage this intuitive interaction to facilitate workspace transitions.

**DC3: Provide responsive and fully interactable data artifacts to minimize the gulf of action.** There are two primary gulfs: the gulf of evaluation and the gulf of execu-

tion [119]. The gulf of evaluation refers to users perceiving the system's state differently than its actual state. To address this, we will provide responsive interactions to update the visual state of the artifacts in both the computational notebook and the embodied space. The gulf of execution refers to users incorrectly interpreting the system's capacity. To address this, we will make the data artifacts fully interactable to match users' expectations. For example, users should not only be able to move a data visualization but also grab a data point within the visualization and delete it.

## 5.3 ICoN for data science

ICoN is a prototype system that facilitates a seamless transition between computational notebooks, data transformation, and visualizations, all within a unified, fully immersive environment. Although computational notebook interfaces in immersive spaces are well-defined, utilizing immersive data science tasks within these environments introduces unique challenges that require both adaptations and novel design considerations. The following discussion details our principal design and implementations made in response to these considerations.

### 5.3.1 Embodied data science workflow

To fully leverage the unique capabilities of embodied interaction in data science tasks, we have integrated an embodied workspace within the system while retaining computational notebooks. This setup allows analysts to explore data more responsively and interactively, which aligns with our considerations for minimizing the gulf of execution (DC3) in ICoN. Below, we detail our considerations for integrating the embodied workspace to facilitate embodied data transformation and visualization.

**Embodied data transformation.** Given the matters in data transformation in existing computational notebooks, our research led us to the work of In et al., who introduced an innovative approach to embodied data transformation [30]. Their approach allows users to directly manipulate data within an immersive space using embodied gestures and additional visualization aids. They highlight that the large display space, a notable benefit of VR, was suitable for performing such gestures. Following this, we believe their findings can be

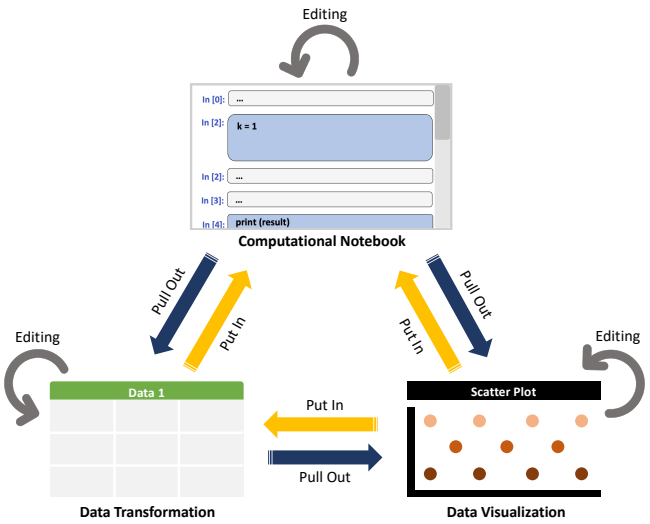



Figure 5.2: Illustration of iterative data science workflow in ICoN.

extended into ICoN, underscoring the importance of intuitiveness in embodied interaction and visual-based direct manipulation of data. This aligns well with our design consideration for embodied data transformation in ICoN, which led us to adapt their approach. All introduced interactions and transformation operations from their approach have been imported into ICoN.

**Embodied data visualization.** Data visualization in computational notebooks is often employed with external libraries like Matplotlib [120], Seaborn [121], or Pandas [122] for their plotting capabilities. However, these libraries require analysts to write extensive code when sophisticated editing or dynamic interaction with visualizations is needed. External applications, such as IATK, have emerged as solutions designed to allow users to dynamically interact with their visualizations without the need to write extensive code [5]. Following their successful exploration, we found that IATK aligns well with our design considerations for embodied data visualization in ICoN; however, we encountered limitations when attempting to import their systems.

The issue was that they employed controller-based interactions, whereas we opted for bare-hand interaction to aim for a more intuitive and immersive user experience. More importantly, the value of exploring visualizations within embodied workspace is well-established. Following this, we considered that integrating their entire system into ICoN is worth nothing without an initial investigation of our primary objectives, leading us to adopt only specific methodologies. In summary, we narrowed to specific visualization types, with an emphasis

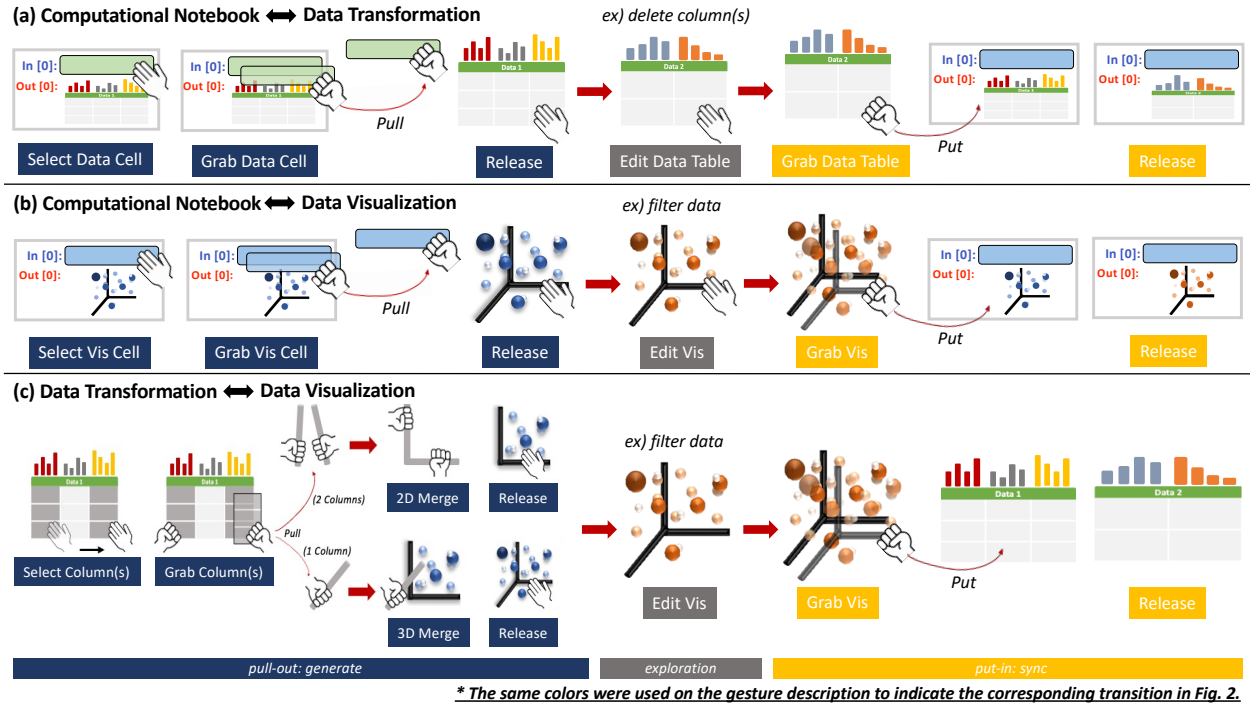



Figure 5.3: Gesture interactions to transit between computational notebooks, data transformation, and data visualizations.

on scatter plots and node-link diagrams, as they have received notable attention in immersive analytics research [68, 123, 124].

### 5.3.2 Seamless transitioning

We initially considered using teleportation, such that users could swipe to teleport to desired workspaces. However, prior research shows that teleportation adds context-switching costs as users must adjust to dramatically changed environments [6]. We concluded that transitions should be spatially connected, ensuring a seamless workflow between spaces. Through design, we found pull-and-put interactions, facilitated by natural grabbing and walking, to be intuitive, allowing users to maintain focus while transitioning between workspaces. We believe this approach fulfills our design consideration of both providing low-effort transitions (DC1) and enabling embodied transitions (DC2). Consequently, we employed pull-and-put interactions for transitioning between computational notebooks, data transformation, and visualizations, as illustrated in Fig. 5.2. In the following sections, we detail the transition mechanism, particularly focusing on interactive transitions, as slight shifts or rotations of

the head and eyes can accomplish navigational transitions.

**Computational Notebook ➡ Data Transformation.**

Transition from *computational notebook* to *data transformation:* the user first needs to select a data cell. The system identifies a data cell when it contains code for importing or assigning datasets. Moreover, we assign a different selection color (marked in green) for data cells in the computational notebook, acknowledging that these cells often do not contain output, making it challenging to differentiate them from other cells. Following this, the user grabs a selected cell and pulls it out. Upon releasing it in the desired position, a data table will be generated, as illustrated in Fig. 5.3-(a)-*pull-out: generate*. As an indicator, the line will be generated between the data cell and the generated data table.

Transition from *data transformation* to *computational notebook:* the user needs to grab the explored data table and put it back into the computational notebook, as illustrated in Fig. 5.3-(a)-*put-in: sync*. The explored data table will be recorded in the computational notebook, and the line indicator will be removed. After that, all the codes in the lower hierarchy will be automatically executed. The details of how the code is recorded are discussed in a later section.

**Computational Notebook ➡ Data Visualization.**

Transition from *computational notebook* to *data visualization:* user first selects a visualization cell. For visualization cells, the same color employed for regular cells has been applied, as it typically entails visualization results beneath the code, making them distinctly identifiable from data and regular cells. Upon selection, users grab, pull out, and release the selected cell in the desired position. The existing 2D or 3D static visualization image in the computational notebook will be generated in an interactive and three-dimensional manner, as illustrated in Fig. 5.3-(b)-*pull-out: generate*. As an indicator, the line will be generated between the visualization cell and the generated data visualization.

Transition from *data visualization* to *computational notebook:* user grabs the explored visualization and puts it back into the computational notebook. The line indicator will be removed, and the explored visualizations will be recorded in the computational notebook, as illustrated in Fig. 5.3-(b)-*put-in: sync*. After that, all the codes in the lower hierarchy will be automatically executed. We specify the code recording process in a later section.

**Data Transformation ➡ Data Visualization.**

Transition from *data transformation* to *data visualization:* users select two columns, grab one with each hand, and merge them. The system then generates a 2D interactive visualization using the chosen columns, as illustrated in Fig. 5.3-(c)-pull-out: generate. As an indicator, the line will be generated between the data table and visualization. The selected columns will be marked in blue to indicate that they have been used for visualization creation. For more complex datasets or to further enhance understanding, users can convert into 3D interactive visualization by selecting an additional data column from the data table and adding it to an existing 2D interactive visualization. In addition, users can also convert in a 2D format by discarding the desired axis.

Transition from *data visualization* to *data transformation:* users grab the explored visualization and put it back into the data table, as illustrated in Fig. 5.3-(c)-put-in: sync. The data table will be updated with the explored visualizations, and the line indicator will be removed.

### 5.3.3 Embodied Low-code programming

The low-code programming approach [2, 16] is known for its rapid application development with minimal manual coding [125, 126]. We envision this approach further reduces the effort required for interactive transitions (DC1) and minimizes the gulf of evaluation (DC3) within ICoN. Therefore, we opted for gestural-based low-code programming, as WIMP interfaces are not suitable for VR [16, 51]. For instance, users can synchronize their explorations of data transformation or visualization into the computational notebook without writing extensive code. Below, we detail the adapted low-code mechanism in ICoN.

**Data artifacts generation mechanism.** To generate data tables within the embodied workspace, we focused on using Python Lists or Arrays [127]. However, we recognized that using a Pandas DataFrame [122], one of the popular data structures, is slightly different due to its ability to contain multiple data types within a single variable. To handle this, we ran Pandas functions to collect data as lists/arrays, such as column names, data values, and data types. To generate data visualizations, we focused on the Matplotlib [120] and Seaborn [121] packages. These packages allowed us to access the data needed for visualizations within the embodied workspace, such as the coordinates of data points, axis names, and clustering colors. We first ran the appropriate functions in Matplotlib or Seaborn to save the required data into the local machine (Unity). Then, we created visualizations by displaying data

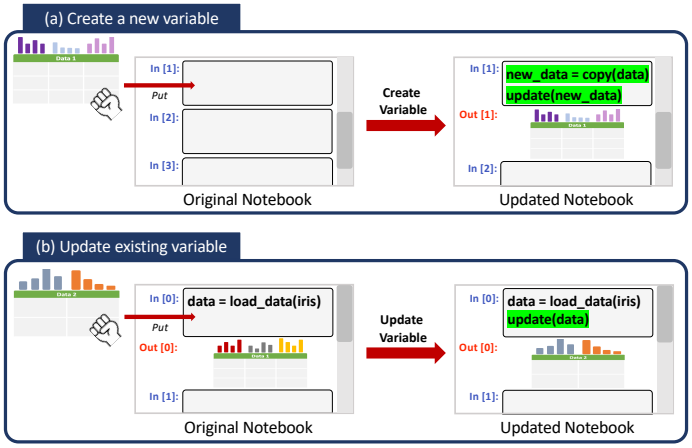



Figure 5.4: Putting transformed data table into a code cell updates the code in the computational notebook. Users can either (a) create a new variable by putting their work into an empty cell, or (b) update an existing variable by putting their work back into a cell that was previously pulled.

points with their proper clustered colors.

**Code generation mechanism—create new variable.** User can "put-in" their explorations into an empty cell. A new variable will be created containing the explored data table or visualization. Code will be created based on the data types (e.g., Pandas or Matplotlib) once the artifacts are generated. The created code does not contain the entire log of the explorations; it only includes the code with the final explorations, as shown in Fig. 5.4-(a).

**Code generation mechanism—update existing variable.** User can "put-in" their explorations into a cell previously used to pull the data table or visualizations. The existing variable will be updated based on the explored data table or visualization. Code will be created based on the data types specified in the existing cell. The created code does not contain the entire log of the explorations; it only includes the code with the final explorations, as shown in Fig. 5.4-(b).

## 5.4 First user study: Usability

We conducted a usability study to understand our system's strengths, weaknesses, and characteristics rather than to evaluate ICoN's effectiveness in comparison to other systems. The primary goal was to determine participants' impressions of seamless transitioning between

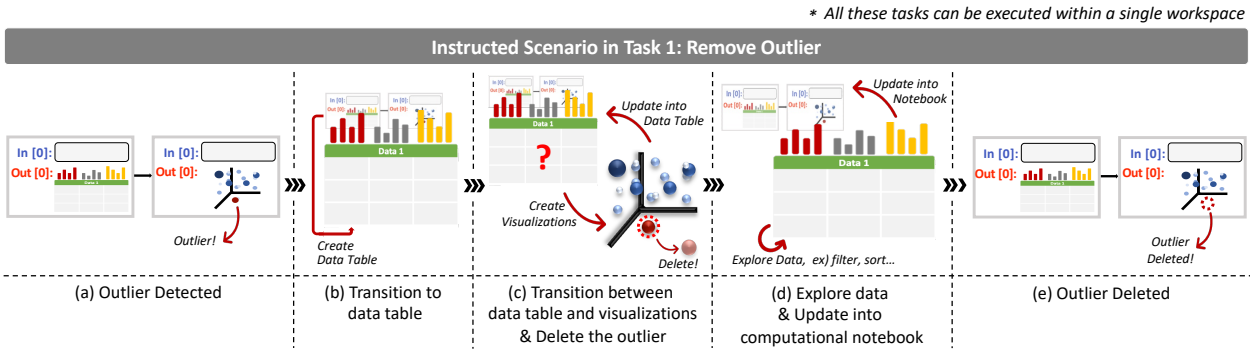



Figure 5.5: A instructed scenario in Task 1 to remove outliers. (a) The user identifies an outlier within a visualization cell that needs to be eliminated from the data cell. (b) To delete the outliers, the user can navigate to the data cell to pull out the data table. (c) Identifying an outlier directly within the data table can be challenging, necessitating the creation of a visualization to pinpoint the outlier. The user can then remove the outlier directly from the visualization, subsequently updating the data table with these changes. (d) Next, they can further explore the data table and put it back into the computational notebook. (e) Finally, the user confirms that the outlier has been successfully removed from the computational notebook.

immersive computational notebooks and embodied data science tasks.

### 5.4.1 Task and Data

Building upon the successful exploration of immersive computational notebooks [16], we emulated their methodologies to maintain our study's focus by simulating a scenario where participants utilized pre-existing code. A KNN (K-Nearest Neighbors) classification algorithm was employed to classify the "iris" dataset in the computational notebook. The official sci-kit-learn documentation [65] was used to load the dataset, and matplotlib libraries [120] were used to visualize the data. The notebook provided two scatter plots: a 2D scatter plot that included outliers and a 3D scatter plot that included misclassified data points. Each visualization was generated from the KNN classification on a specific parameter value.

With those computational notebook setups, we designed two tasks reflecting real-world data analysis scenarios. Our objective was to evaluate the integration of embodied data transformation and visualizations into computational notebook environments, with a particular emphasis on its transition capabilities. To achieve this, participants were tasked with frequent transitions between computational notebooks, data transformation, and visualization.

Specifically, the *Task 1* is designed to concentrate on embodied data transformation, while *Task 2* focuses on embodied data visualization. The specific tasks of the study, formulated within this context, are detailed below.

**Task 1. Remove outlier.** In this task, step-by-step instructions were provided to participants to fully leverage the available feature in ICoN. The task started with participants identifying outliers in a 2D scatterplot within computational notebooks. After being informed to remove outliers from imported datasets, they first extracted a data table and attempted to delete them from the data table; however, relying solely on data tables can be very challenging. Therefore, we instructed them to generate visualizations for easier outlier identification. Following this, we asked them to identify and remove outliers from this visualization and subsequently update the data table with their explorations. This approach was chosen to enable participants to have more experience in transitioning. They were also briefed on necessary data transformation steps to format the data table correctly. The final step involved updating the computational notebook with the transformed data table and verifying that the outliers have been removed from the 2D scatterplot. The visual description of these instructions is illustrated in Fig. 5.5.

**Task 2. Inspection.** Following Task 1, we introduced Task 2, asking participants to complete the tasks without specific instructions. Participants were initially informed that the 3D scatter plot is generated with different parameter values and contains fewer data points than those in Task 1, including a misclassified data point. Then, we asked to identify and delete the misclassified data point by comparing it with the 2D scatter plot, which was corrected in Task 1. For a more effective comparison, users had options to convert them into the same dimension. We intentionally designed these visualizations in different dimensions to test the interaction capabilities within visualizations in computational notebook settings. After identifying and removing the misclassified data points, participants were expected to update the computational notebook with the visualizations they had explored. The study concluded once participants successfully updated the notebook with the corrected classifications.

### 5.4.2 Experimental Setup

We recruited 10 participants (9 male, one female, ages 18 to 35) through a university mailing list, selecting individuals based on their familiarity with data science, machine learning

algorithms, and experience with computational notebooks (e.g., Jupyter Notebook). Regarding VR experience, 9 participants reported having experience with using VR, while the remaining one indicated no prior experience with VR technology. All participants had either normal vision or corrected vision to normal standards.

The study was conducted with the Meta Quest Pro headset, with a resolution of $1800 \times 1920$ pixels per eye and a refresh rate of 90Hz. This headset was linked to a PC equipped with an Intel i7-11800H processor operating at 2.30 GHz and an NVIDIA GeForce RTX 3070 graphics card. The Meta Air Link feature facilitated a cable-free experience, leveraging the PC's computation power while the headset managed the rendering. This configuration allowed participants to navigate a $16m^2$ space freely. Initially, participants were placed at the center of this space, surrounded by ten notebook windows, each measuring $0.35x0.30m^2$, arranged in a semi-circle at a distance of $1m$ from them.

### 5.4.3 Procedure

Participants were first welcomed and reviewed a consent form, followed by a brief overview of the study's objectives and procedures. They were then given enough time to adjust the Quest Pro headset before they started the training session. This stage ensured participants were in comfortable conditions and could clearly see all the text. Then, participants proceeded to the training stage. In this stage, we verified their understanding of the system. After confirming their understanding of the system, participants moved on to the study task. To ensure a comprehensive understanding, we provided detailed context about the algorithms and the tasks to be completed. Participants had no time limit for task completion; they were instead encouraged to focus on accuracy and efficiency. After the study task, participants filled out a Likert-scale survey, including the System Usability Scale (SUS) and the NASA Task Load Index (TLX), to capture their subjective experiences. They were also asked to provide qualitative feedback on the system's pros and cons. On average, the study took less than an hour, and to thank participants for their time and contribution, we provided a $10 Amazon Gift Card.

### 5.4.4 Results

We first present the results and metrics, followed by the completion of the SUS and NASA TLX to assess subjective experiences. We then discuss ICoN's strengths, characteristics, and areas for improvement.

**Ratings.** Participants significantly favored ICoN with an average of 6.3 out of 7.0 in impresivness and 6.5 out of 7.0 in their preferences. Additionally, participants reported that ICoN was *easy to use* (average 4.1 out of 5), they would like *to frequently use the system* (4.1 out of 5), various functions were *well integrated* (4.6 out of 5), and *minimum effort* (4.3 out of 5) was required to learn how to use those functions. To this end, ICoN got 78.25 of average SUS score and in between the 80-84 percentile, indicating that the system is "Acceptable" with "Excellent" adjective rating [128].

**Qualititative Feedback.** To systematically analyze insights from user feedback, we developed a qualitative coding scheme that involved identifying recurring themes within the feedback. We present the top codes alongside other associated codes (with frequencies out of 10 in parentheses). ICoN was praised for offering a *smooth transition* (5), characterized by *intuitiveness* (5) on their interactions. They specifically highlighted *effective data transformation* (7) and *efficiency of embodied data visualizations* (7) within computational notebook settings, as it allows *direct manipulation* (2). Additionally, participants were highly favored of *writing less code* (8), which allows *skipping processes* (4) required in traditional notebooks, and *embodied interaction found to be effective* (2) in low-code approach. Notably, the embodied low-code was also seen as further supporting a *smooth transition* (3). However, all participants reported several minor *technical* challenges, particularly regarding Meta's gestural recognition capabilities on pinch interaction. Additionally, concerns were raised about *physical fatigue* (4) and the relatively *small workspace* (2) on performing tasks.

## 5.5 Redesign

While several visualization aids were implemented in ICoN to clarify the relationships among various tasks, participants encountered difficulties in recalling their workflow, particularly in non-hierarchical structures. This indicates that the provided visual representations of the workflow needed to be improved. The concept of a data flow system, initially devel-

oped as a graphical approach for system analysis [129], enhances analytical capabilities by clearly representing complex workflows with arrows and small multiples [130]. Building on their successful explorations, previous studies introduced linking mechanisms into immersive computational notebooks [16], which allowed participants to follow workflows more easily. We then applied such linking mechanisms across all tasks in ICoN, which will further clarify the relationships and support maintaining a focus on their workflow, even when the spatial relationships are not apparent.

## 5.6 Second User Study: Evaluation

To systematically evaluate the effectiveness of ICoN, we designed a controlled user study focusing on ICoN's two unique key characteristics—an immersive and unified workspace. These characteristics result in two primary factors we want to investigate in the study.

To understand the potential benefits of having an immersive space for data analysis, we consider the computing environment as one of the primary factors. Specifically, we aim to compare an immersive environment versus a non-immersive environment (i.e., using a desktop in our case). Although comparisons of immersive and non-immersive environments have been studied in various contexts, it is widely recognized that more empirical research is needed in immersive analytics [3].

To understand the potential benefits of the seamless transition between a computational notebook and an embodied workspace, we consider the workspace configuration as the other primary factor. Specifically, we compare a unified workspace, where the computational notebook and embodied workspace are in the same physical space, with a separated configuration, where participants can access only one at a time. While a unified workspace can reduce context-switching costs, it may become cluttered, affecting usability. Conversely, separated workspaces can reduce clutter but may increase the cognitive load of switching between spaces.

To systematically address these trade-offs, we aim to answer two key questions:

- What advantages does an immersive environment offer for data analysis compared to a traditional desktop (Desktop vs. VR)?
- What are the impacts of unifying computational notebooks and embodied spaces into

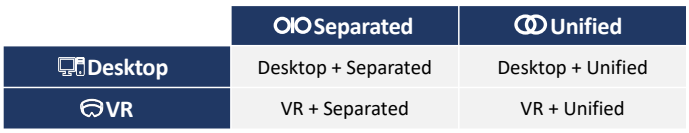



Figure 5.6: Our study focused on two primary comparison factors, leading to four testing conditions.

a single environment compared to managing them separately (Separated vs. Unified)?

Therefore, this study involved four conditions: Desktop+Separated, Desktop+Unified, VR+Separated, and VR+Unified (see Fig. 5.6).

### 5.6.1 Study Conditions

In the following, we detail our implementations applied to each experimental factor. The illustrations of testing conditions are provided in Fig. 5.7.

**Desktop.** In the Desktop, we used a mouse and keyboard to emulate standard computational notebooks and data science tools. Users could freely display computational notebooks and data artifacts by dragging. Specifically, we employed the interactive embedded (desktop screen-based) workspace [77, 118], which allows for simple dragging to explore visualizations (e.g., 3D scatter plots) from various angles, to best simulate the exploration capabilities provided by the embodied workspace in VR. For other interactions, we adhered to standard WIMP designs: users utilized the mouse to select targets and click buttons to execute operations for computational notebook, data transformation/visualizations, and transitioning between workspaces, as illustrated in Fig. 5.7-(a) and (b).

**VR.** In the VR, we opted for bare-hand interaction over using physical devices to provide a more intuitive and immersive user experience. However, as In et al. found, employing WIMP-based virtual keyboards remains a significant challenge in the use of immersive computational notebooks [16]. Therefore, we decided to use a physical keyboard, employed in a movable and adjustable-height desk. Recognizing that carrying and typing on a physical keyboard while navigating in VR can potentially reduce spatial exploration [50], we supported participants by rearranging the desk for them as needed. This setup ensured that they could freely navigate the space while having access to the keyboard whenever required. Additionally, the initial size of the computational notebook and data artifacts was adjusted and tested with

different sizes to ensure readability from a distance. Illustration of **VR** is shown in Fig. 5.7-(c) and (d).

**Separated.** In the SEPARATED, the transition focus is on the workspace; the workspace will be shifted to another workspace for users. Therefore, only one of the computational notebooks or data artifacts is visible at a time, which ensures sufficient display space, although each is spatially disconnected (see Fig. 5.7-(a) and (c)). While WIMP interactions invoke transitions in DESKTOP+SEPARATED, we utilized physical walking interactions to minimize the teleportation involved in the transition process. Specifically, data artifacts will be generated in front of participants when they walk into a data or visualization cell, and they can then transition back to the notebook space by walking through a portal positioned behind them. In both DESKTOP and **VR**, interactive transitions involve holding data artifacts, whereas navigational transitions are made without holding data artifacts while walking through the cell or portal.

**Unified.** In the UNIFIED, the transition focus is on the user, who needs to transition themselves to another workspace. Therefore, the computational notebook and data artifacts are visible at a time and spatially connected within a single environment, though this results in a smaller workspace (see Fig. 5.7-(b) and (d)). While WIMP interactions were used to invoke transitions in DESKTOP+UNIFIED, physical arm interactions (put-in/pull-out) were utilized for interactive transitions in **VR+UNIFIED**. Navigational transitions could made by changing their viewpoint through head rotation, eye movement, or walking. Our design of ICoN (**VR+UNIFIED**) is presented in Sec. 5.3.

### 5.6.2 Data and Task

Building on the initial evaluation of immersive computational notebooks [16], we simulated a scenario with pre-existing code (14 notebook windows and 30 cells). To mitigate learning effects, we used four datasets from the scikit-learn [65] Python package: diabetes, wine, iris, and breast cancer. A 2D scatter plot was provided for a brief overview of data, while a 3D node-link diagram was utilized to visualize information from neighboring nodes to capture complex relationships. We applied K-Means for clustering and K-Nearest Neighbors (KNN) for visualizing relationships in node-link diagrams, often referred to as KNN graphs that play a significant role in web-based search [131] or recommendations [132]. With this setup, we structured two tasks to evaluate interaction efficiency and identify the trade-offs.

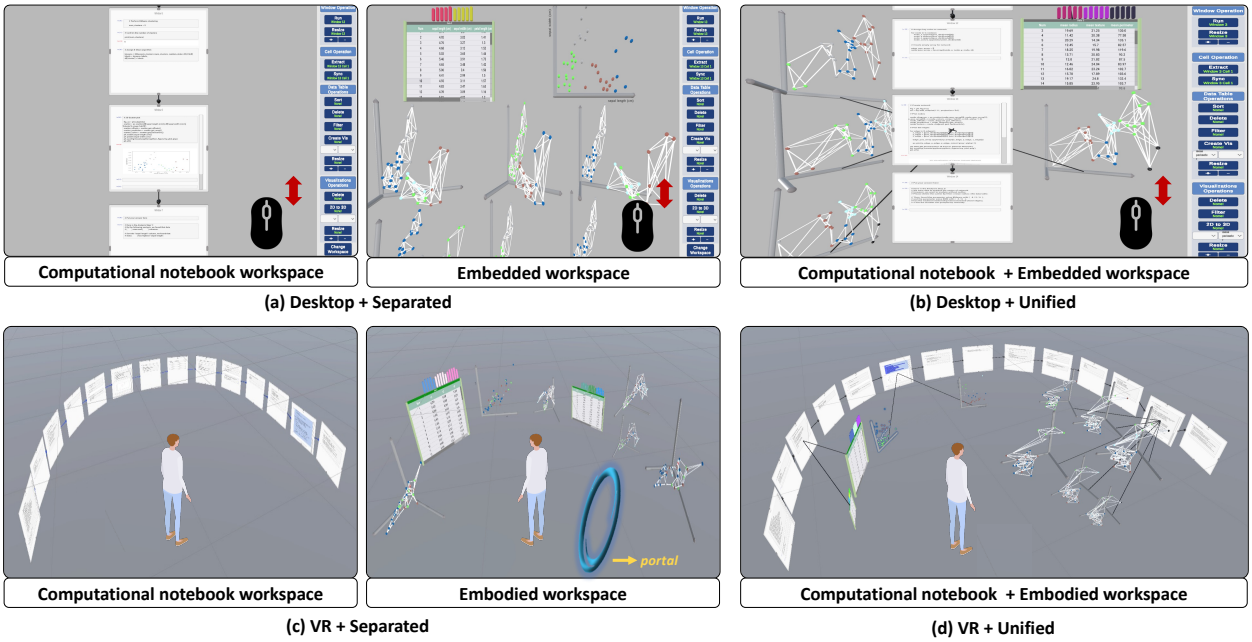



Figure 5.7: Illustration of tested conditions in our study. In the DESKTOP (top), users navigate by scrolling, while in the VR (bottom), they navigate by walking and rotating their heads. Additionally, the computational notebook and embedded/embodied workspace are spatially disconnected in the SEPARATED (left), whereas in the UNIFIED, they are spatially connected (right).

**1. Instructed task.** In this task, we provided step-by-step instructions to assess the interaction efficiency of our tested variables to ensure that the results were not influenced by other factors (e.g., the sense-making process). The task began with participants understanding the dataset. First, they generated a data table and navigated through it to find the number of rows and columns. Next, they sorted to find a specific column's lowest and highest values. Participants were then required to document their analysis in the computational notebook. Subsequently, they converted a 2D scatter plot to a 3D scatter plot by generating the 2D scatter plot from the computational notebook and adding an additional column from the data table to the existing plot. The final step involved syncing the 3D scatter plot into the computational notebook.

**2. Exploratory task.** Following the instructed task, we introduced an exploratory task without specific instructions to identify the trade-offs of immersion and unification on exploratory data science tasks. They were informed that the goal was to remove outliers and fine-tune the employed machine learning algorithms (K-Means and KNN) to perform simple data analysis with a 3D node-link diagram. Specifically, we explained that outliers could only be deleted by filtering specific columns on the data table they interacted with in the instructed task. In addition, analyzing results from different parameter values in K-Means and KNN required the embodied workspace, as not all data points on the static 3D node-link diagram image would be visible in the computational notebook. We informed participants that the column names and testing parameter value ranges were also available in the computational notebook. Therefore, participants needed to iteratively transition between the computational notebook and the embodied workspace to remove outliers and analyze the results from different parameter values. The task was completed when participants successfully deleted the outliers and identified the optimal parameter pairs.

### 5.6.3 Participants and Apparatus

We recruited 20 participants (16 male, 4 female, ages 18 to 35) from a university mailing list, selecting individuals based on their familiarity with data science, machine learning algorithms, and computational notebooks (e.g., Jupyter Notebook). Regarding VR experience, 14 participants had used VR, while the rest had no prior experience. Six of the VR-experienced participants used VR weekly. All participants had normal or corrected-to-normal vision.

For Desktop, we used a single monitor to reflect better analysts' needs for repeatedly switching between multiple data science tools when all tools cannot be displayed simultaneously across multiple monitors. Specifically, we used a 27" monitor with a 2560x1440 resolution, and the notebook windows were centered on the screen, allowing participants to view two or three simultaneously. Vertical scrolling was incorporated to navigate within both the computational notebook and embedded workspace. Specifically, on the left and right sides, empty spaces were provided for displaying generated data artifacts in Desktop+Unified. This setup was mirrored in Desktop+Separated for consistency.

For VR, we used the Meta Quest Pro headset with a resolution of $1800 \times 1920$. It was linked to a PC with an Intel i7-11800H processor and an NVIDIA GeForce RTX 3070 graphics card. Meta Air Link provided a cable-free experience, utilizing the PC's computational power while the headset handled rendering. This setup allowed participants to navigate a $25m^2$ space freely. Participants started in the center of this space, 1 meter from a pile of cells each measuring $0.35x0.30m^2$. A movable desk with a keyboard was initially placed in front of them.

### 5.6.4 Procedure

Our user study employed a full-factorial within-subjects design, balanced using a Latin square with four groups. The study took less than two hours on average. Participants were first welcomed and reviewed a consent form. We ensured proper adjustment of chairs and headsets for clear text visibility. We then began with training sessions and standardized terminology in computational notebooks. The training was provided when participants encountered every study condition. Recognizing VR's unique challenges, we extended training to allow participants to become familiar with the immersive environment, addressing potential issues like physical discomfort and learning curves. The training concluded once participants achieved task proficiency, typically taking 15-20 minutes. After training, participants proceeded to the study task (details in Sec. 5.6.2). After each condition, they completed a Likert-scale survey, adapted from the System Usability Scale (SUS) and NASA Task Load Index (TLX), to document their subjective ratings. We also collected qualitative feedback on the condition's advantages and disadvantages. The study concluded once participants completed the questionnaires for all conditions.

### 5.6.5 Hypothesis

We formulated hypotheses based on prior explorations, and our analysis of the study conditions outlined in Sec. 5.6.1.

**Transition in Desktop and VR.** VR allows for embodied transitions within a large display space, enabling participants to transition by physically walking, rotating their heads, and through gestures. Therefore, we anticipated that VR would encourage more frequent transitions ($H_{env-trans}$) for both interactive and navigational, as previous studies have demonstrated that physical navigation is more effective and intuitive than virtual navigation on a Desktop [16, 32]. However, previous studies have shown that interactions involving more physical movement can result in longer completion times [133]. Therefore, we hypothesized that the Desktop would result in faster completion times. ($H_{env-time}$).

**Transition in Unified and Separated.** We anticipated that the Unified would facilitate more transitions compared to the Separated ($H_{space-trans}$) for both interactive and navigational transitions. In the Unified , the computational notebook and data artifacts are visible simultaneously, enabling effortless transitions by simply moving the eyes or the head. In contrast, the Separated requires extra steps to change workspaces by clicking a button or walking in/out of the space. We also anticipated that these additional steps would result in longer completion times ($H_{space-time}$).

**Workspace managements.** We expected the larger display space in VR to reduce the need to relocate content to manage the workspace ($H_{env-reloc}$), as the large space allows participants to organize structures without much efforts [30]. Additionally, we anticipated that this larger space would allow participants to delete less and keep more data artifacts compared to Desktop ($H_{env-del_left}$). Conversely, we predicted that the spatially dense workspace in the Unified would require more frequent content relocation to maintain enough space ($H_{space-reloc}$). As a result, we also expect deleted more data artifacts and fewer data artifacts to be left in Unified ($H_{space-del_left}$). However, we expected that Unified would reduce mental demand ($H_{space-mental}$) by allowing related artifacts to be displayed in close proximity and spatially connected, which aids users in remembering the locations of previously visited cells/artifacts.

### 5.6.6 Measures

We collected quantitative data and interaction records for each study condition to evaluate our hypothesis. Specifically, we used the following measures; **Time:** we measured the time from the initial exploration of the system to task completion. **Number of transitions:** we recorded the total number of transitions per minute to task completion. For details on the types of transitions we considered, please refer to DC1 in Sec. 7.2. **Number of contents relocations:** we recorded the total number of contents relocations whenever the user moved either computational notebook or data artifacts. **Number of performed delete operations and data artifacts left:** we documented the number of data artifacts and number of performed delete operations when the participant completed each study trial.

We also collected subjective ratings on a seven-point Likert scale for **mental demand**, **physical demand**, and **engagement**. Participants also **ranked** their overall experience. **Qualitative feedback** about each condition's pros and cons were also collected from participants.

### 5.6.7 Results

This section presents the results of our statistical analysis, along with a summary of qualitative feedback for each condition. We identified statistical significance at the following thresholds: $p < 0.001(***)$, $p < 0.01(**)$, $p < 0.05(*)$, and $p < 0.1(\cdot)$. In addition, we report the mean values with a 95% confidence interval (CI) and use Cohen's d to measure the effect sizes of significant differences. Detailed statistical analysis results are provided in the supplementary materials.

#### Quantitative Results

We noted that participants completed the study tasks without significant trials to complete the study task, leading to no variation in accuracy. The following sections present results that emphasize performance differences across the conditions. Results are illustrated in Fig. 5.8, Fig. 5.9, and Fig. 7.7.

**Time.** We measured the instructed task's completion time to assess interaction efficiency across conditions. Our analysis showed that time was significantly affected by both the




Figure 5.8: Completion time and transition count across conditions: (a) and (b) indicate the time taken to complete each task. (c) shows the total number of transitions, while (d) shows the interactive transitions, and (e) shows the navigational transitions count. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below display effect sizes for pairwise comparisons, with black-bordered squares highlighting the outperforming conditions.

computing environment (∗∗) and workspace configuration (∗ ∗ ∗). On average, Desktop had 19.3% faster completion times than VR: 145.3s for Desktop+Separated vs. 164.4s for VR+Separated, and 83.5s for Desktop+Unified vs. 114.5s for VR+Unified. The Unified was also faster, being 74.0% faster on Desktop and 43.6% faster in VR. However, in the exploratory task, these patterns shifted: VR had faster completion times than Desktop in the Separated , with 771.6s for Desktop+Separated vs. 563.0s for VR+Separated, and 420.3s for Desktop+Unified vs. 429.9s for VR+Unified. While patterns have been shifted within a computing environment, the workspace configuration remained consistent (∗ ∗ ∗). The Unified was consistently faster than the Separated, 45.5% faster on Desktop and 23.6% faster in VR. Therefore, we reject $H_{env-time}$ and accept $H_{space-time}$.

**Number of transitions.** Our findings indicate that both computing environments and workspace configurations significantly impacted the total transitions and navigational trasitions (∗ ∗ ∗), however only computing environments had statistical significance (∗ ∗ ∗) with interactive transitions. We observed that the Desktop had more total transitions than VR, with an average increase of 66.5%. Specifically, we observed similar patterns in interactive and navigational transitions, with increases of 10.1% and 46.0%, respectively. In addition, the Unified had more total transitions than the Separated in both Desktop and VR. Specifically, participants made 4.2 total transitions in Desktop+Separated and 4.7 in Desktop+Unified, reflecting an 11.9% increase. This pattern was also observed in VR, with 2.2 total transitions in VR+Separated and 3.3 in VR+Unified, representing a 50.0% increase. While navigational transitions showed a similar pattern, with a 65.2% increases in Desktop and a 56.4% increases in VR, the patern were shifted in interactive transitions: Desktop decreases of 17.2%, whereas VR increases of 21.6%. Therefore, while we both reject $H_{env-trans}$ and $H_{space-trans}$ for interactive transitions, reject $H_{env-trans}$ and accept $H_{space-trans}$ for navigational transitions.

**Number of contents relocations.** We could only find significant effects from the computing environment (∗ ∗ ∗) and the number of content relocations. Participants made fewer content relocations in VR, averaging 1.27 times, compared to 6.21 times on the Desktop, showing a reduction of 79.55%. Additionally, we found that participants relocated slightly more in the Unified, with an increase of 4.78% in Desktop (6.07 times in Desktop+Separated and 6.36 times in Desktop+Unified) and 19.3% in VR (14.0 times in VR+Separated and 11.3 times in VR+Unified). Therefore, we accept $H_{env-reloc}$, but reject $H_{space-reloc}$.

**Number of performed delete operations and data artifacts left.** We observed a

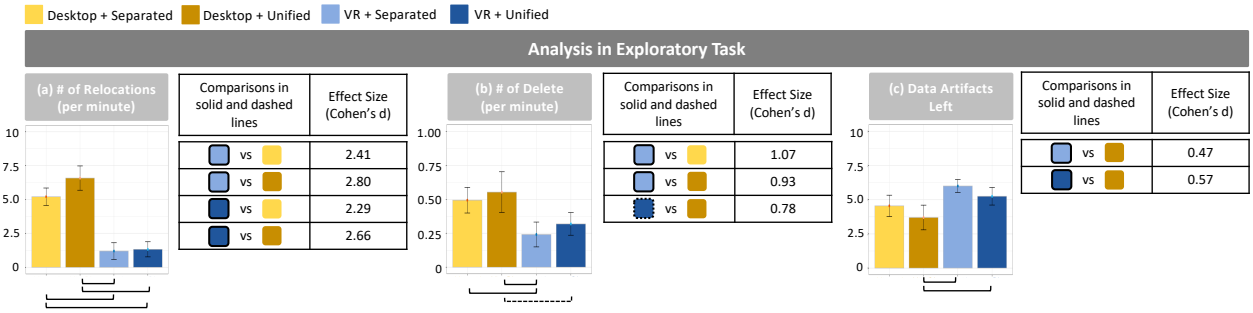



Figure 5.9: Measurements of (a) number of relocating computational notebooks and data artifacts, (b) number of deletion operations performed, and (c) amount of content left in the given environment. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below show effect sizes for pairwise comparisons, with black-bordered squares highlighting the outperforming conditions.

significant impact of the computing environment ($***$) on both the number of deletion operations performed and the number of remaining data artifacts. However, the workspace configuration ($*$) only had a marginal impact on the number of data artifacts left. Participants deleted fewer and kept more data artifacts in **VR** (avg. 0.3 and 5.6) compared to **Desktop** (avg. 0.5 and 4.5). Furthermore, participants deleted more and kept less in **Unified** (avg. 0.43 and 4.6) compared to **Separated** (avg. 0.36 and 5.5), but did not have significant effects. Therefore, we accept $H_{env-del_left}$, but reject $H_{space-del_left}$.

**Ratings and ranking.** Significant effects were observed across mental demand ($***$), physical demand ($***$), and engagement ($***$). **VR** were more physically demanding than **Desktop** but showed higher levels of engagement. **Unified** outperformed in terms of mental demand, physical demand (particularly in **VR**), and engagement. Therefore, we accept $H_{space-mental}$. In terms of engagement, **VR+Unified** was the most engaging condition, with an average rating of 6.25 out of 7 and a confidence interval of 0.45. In addition to subjective ratings, the **VR+Unified** was the most preferred for performing data science tasks, with 15 participants ranking it first ($***$). No participants preferred the **Desktop+Unified**.

### Qualitative Feedback.

We performed a qualitative analysis to identify recurring themes in user feedback across each condition. Two authors developed a coding scheme based on feedback from the first five participants, which was then consistently applied to all subsequent data. Finally, we

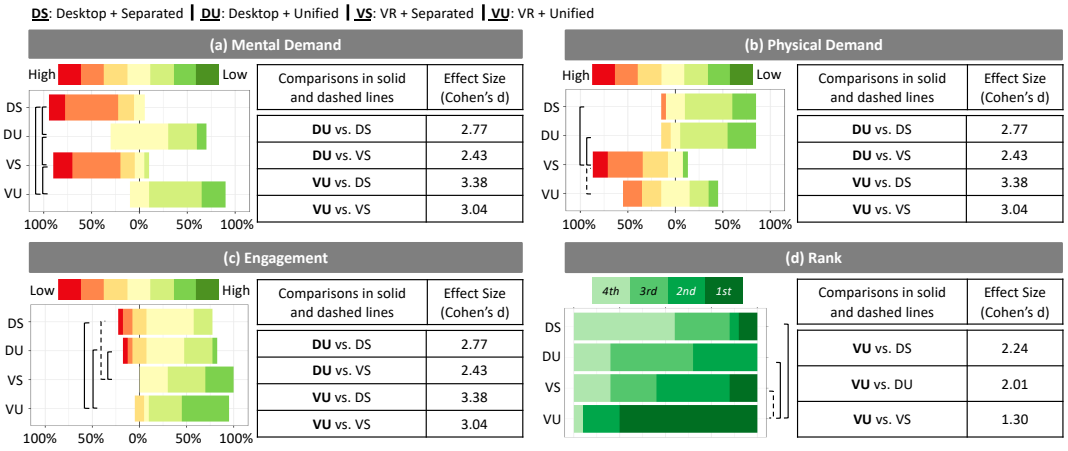



Figure 5.10: Participants' responses: (a) mental demand, (b) physical demand, (c) engagement, and (d) overall user experience ranking. Solid lines indicate statistical significance with $p < 0.05$, and dashed lines indicate $p < 0.1$. The tables below display effect sizes for pairwise comparisons, with bold text highlighting the outperforming conditions.

synthesized the key insights across all conditions. Detailed coding results are provided in the supplemental materials.

**Desktop + Separated.** The majority of participants praised the ability to *write less codes* (11). They appreciated the *flexible and interactive* (5) data exploration, which made it *easy to analyze* (4). In addition, some noted *better engagement* (3) as only a single content type was available. However, most raised concerns about *mental demand* (12), particularly due to *workspace separation* (4). We also found participants to have *unfavorable workspace separation* (8) and *hard to organize* (6) in DESKTOP. Additionally, participants were concerned about using *difficulties of WIMP interactions* (4) for transitioning between workspaces.

**Desktop + Unified.** Unlike DESKTOP+SEPARATED, participants *preferred the unified workspace* (13). They found that moving their eyes enabled *effective transition* (5) and *reduced mental load* (8). Specifically, they reported that unification allowed them to *skip steps* (5) required in the SEPARATED, *save time* (4), and made it *easy to analyze* (3). They also noted that they could *better follow the workflow* (3) using the line indicator. However, participants had concerns about the *limited workspace* (11), leading to a *cluttered workspace* (6) and *difficulties in managing workspace* (6), which made *hard navigation* (4).

**VR + Separated.** Participants favored *flexible workspace management* (14), attributed to the *large display space* (11). They reported that *easy to analyze* (10) due to *intuitive* (7) physical interactions and *easy navigation* (6), which *reduced mental load* (6). However,

many participants expressed concerns about *ineffective transitions* (10) caused by *physical fatigue* (9). Some even mentioned that the transition experience was *better on* Desktop (4). In addition, a few participants pointed out *technical issues* (3), such as pointer interaction.

**VR+Unified.** In contrast to VR+Separated, participants reported *effective transitions* (12) and *preferred the unified workspace* (8). They also reported that the *large display space* (11), *easy to analyze* (6), *reduced mental load* (6), *intuitive* (5) physical interaction, and *flexible workspace management* (5). However, some participants expressed concerns about *difficulties in managing the workspace* (4), noting that the *limited workspace* (3) led to *cluttered workspace* (3). Additionally, they mentioned *technical issues* (3).

## 5.7 Key Findings, Observations, and Discussions

### 5.7.1 Usability Study

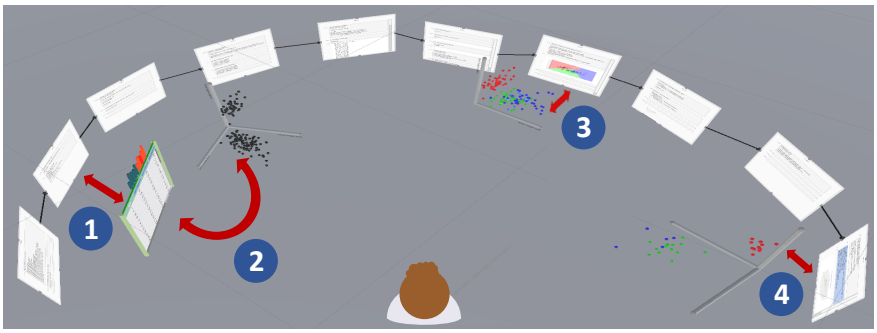
**Embodied data visualization within the computational notebook settings further enhances data analysis performance.** Participants almost always directly initiated compare visualizations within the embodied workspace in Task 2. In contrast, few initiated such comparisons within computational notebooks, leading them to make additional efforts, such as rearranging notebook windows to conduct side-by-side comparisons. Although such comparison was also utilized within the embodied workspace, participants found relocating the entire notebook window solely for this purpose to be inefficient, as it sometimes contained codes less relevant to the comparisons. More importantly, they encountered difficulties with performing a deep and comprehensive analysis of 3D visualizations within a computational notebook, as numerous data points in 3D scatter plots were obscured by others, requiring analysis from various angles to achieve full visibility. Consequently, participants extracted the flat visualizations into an embodied workspace, enabling more dynamic interactions and intuitive comparisons.

Seven participants highlighted the enhanced interactivity in embodied workspace, for example, "It was great that I could see the graph in three dimensions, and I could analyze the data more effectively since I have more interactivity (P5)." Furthermore, the ability to author and interact with visualizations was identified as a significant improvement over traditional notebooks, as highlighted by a participant: "I can extract 3D visualizations and interact with

them easily, which is most preferable interaction since this is very limited in traditional notebooks (P3)." Therefore, we can reasonably say that ICoN is shown to enhance data analysis performance by introducing embodied data visualizations within computational notebook environments. Nonetheless, future research should explore various visualizations across a broader range of analytical tasks to confirm these findings.

**Immersive computational notebooks serve as a spatial anchor.** A noteworthy observation was that nearly all participants refrained from rearranging the computational notebook's initial layout; in contrast, they actively reorganized contents within the embodied workspace. We believe that computational notebooks act as stable reference points in immersive space that maintain the positioning and context of spatial content across different activities [134, 135]. Furthermore, we noted that all participants utilized depth to build their workspace, particularly when the interaction was made from the computational notebook. They positioned data tables or visualizations in front of the corresponding code segments, creating a hierarchical structure, as shown in Fig. 5.11-(a.1 and 3-4). However, such use of depth was not evident in interactions that did not involve the computational notebooks. Specifically, when participants aimed to enhance their understanding of data tables through visualization, they positioned these visualizations at the same depth level as the data tables, leading to a non-hierarchical structure, as shown in Fig. 5.11-(a.2). From these observations, we considered that computational notebooks are a foundation for constructing a hierarchical layout.

**Hierarchical semi-circular layout using the depth cue limits the available space.** We adhere to a semi-circular layout over flat and full-circle designs, followed by successful explorations on effective space utilizations [33, 60]. However, unlike previous studies [30, 50], our study revealed that a few participants did not favor the given layout, particularly concerned with "small display spaces". Building on our previous discussion about the hierarchical relationship between the computational notebook and the embodied workspace, our analysis further demonstrated that adding an extra hierarchical layer to the semicircular layout reduced the workspace size, as depicted in Fig. 5.11-(b). While creating these layouts helps them better follow the workflow, it simultaneously restricts participants' mobility within the space. This observation is in line with participant feedback, "I think the given space was a bit smaller than I expected (P1)." Furthermore, our findings indicated that this observation introduces the additional need for physical movements, such as cleaning the workspace to maintain sufficient working space in a constrained environment. Few participants com-




(a) Process of creating workflow



(b) Created hierarchical workflow

Figure 5.11: A bird's eye view of the layout strategy in ICoN. Participants manage their workspace in a layered hierarchy. (a.1) participants pull out a data table and position it at a closer depth, (a.2) while the visualizations derived from that data table are placed at the same depth. (a.3-4) repeated processes with other visualizations. (b) This results in the creation of a hierarchically structured workflow.

mented about this perspective with potential improvements, "I don't like walking much. I would like to pull out/put back the object from a far distance so that I can keep my space clean all the time without much effort (P3).", and "It would be nice to shrink the entire environment (P1)." Although body movement-based interactions provide seamless transitions, they highlight the need for novel interaction techniques when the user needs to manage and engage with multiple complex tasks simultaneously. Therefore, further investigation into layouts and navigation, emphasizing the importance of hierarchical relationships, appears necessary to guarantee a sufficient or resizable workspace.

**Challenges in tracking embodied activities.** In our study on embodied low-code programming, generally performed after data exploration, participants were required to trace back their workflow and accurately update it into designated tasks. However, we observed that navigating to identify such tasks within a non-hierarchical workflow (e.g., see Fig. 5.11-(a.2)) poses challenges. Despite the fact we instructed participants to first explore visualizations and then update data tables accordingly, some attempted to update the computational notebook, which required reminding the instructions. We believe that participants find it challenging to track all the required information and steps simultaneously after spending considerable time on explorations. Furthermore, we propose that non-hierarchical workflow places additional burdens on participants' memory capabilities to recall and trace back their workflows as spatial relationships have been diminished. This observation was also noted in the previous study by In et al., where participants experienced challenges in recalling performed operations within their workflow, attributed to weakened spatial relationships in desktop environments [30]. However, our observations revealed that participants were able to accurately track their workflow within hierarchical structures. This highlights the significance of hierarchical relationships and reinforces the need for a workspace that continuously supports the creation of a depth hierarchy.

Despite these challenges, it is important to highlight that no feedback was reported about difficulties in performing gestural interactions within such complex workflows. Furthermore, one participant particularly praised the embodied low-code approach, noting, "I think the low-code approach works really well, I had no issues performing those embodied interactions. It really helps me have smooth transitions between notebooks, transformations, and visualizations (P3)." This feedback further underscores the potential benefits of embodied low-code programming in facilitating intuitive and seamless interaction, especially transitioning within code-based applications.

### 5.7.2 Evaluation Study

**Unified accelerates time performance.** We observed that the Unified was consistently faster than the Separated in both instructed and exploratory tasks, as shown in Fig. 5.8-(a) and (b). We noted that the embodied transition enabled participants to complete tasks faster (five) by allowing them to skip steps (four), specifically in navigational transitions, which often required revisiting target objects to recall information. As expected, in the Unified, transitions were facilitated by simply moving eyes or heads, while the Separated required switching entire workspaces, adding extra steps [6], and consequently increasing the time required to complete those steps. Subjective ratings also confirmed that Unified provided better transition compared to Separated, with nine participants preferring Desktop+Unified and twelve preferring VR+Unified. As one participant noted, "I could skip steps in transitioning between workspaces and save a lot of time (P12)." Therefore, we confirmed that the Unified enables more effective transitions.

**Mixed results were observed in time performance across the exploratory tasks between Desktop and VR.** We found that the Desktop was faster than VR for instructed tasks (see Fig. 5.8-(a)), consistent with previous findings that body movement results in longer completion times [3, 106]. However, for exploratory task, VR was faster in Separated and had similar times to Desktop in Unified (see Fig. 5.8-(b)). We believe the sense-making process largely influenced the performance in the exploratory task, as it required participants to think more critically. This supports previous studies showing that immersive environments enhance analytics performance [50] and promote strategic thinking [30], leading to faster completion times. Our study re-confirmed this, as illustrated by a participant's comment: "It was easy to organize data artifacts effectively, and I can compare easily (P2)." In summary, we found that VR is considerably fast for performing complex data analysis tasks.

**Low-effort transition potentially reduced the cognitive load in data analysis.** We observed that transitioning in Unified significantly lowered the mental load, as shown in Fig. 7.7-(a). We believe the need to memorize and retrieve information was replaced by the ability to quickly transition and check information, resulting in more total transitions in the Unified than Separated for both interactive and navigational transitions (see Fig. 5.8-(c), (d), and (e)). Notably, the transition counts were distinct when assessing navigational transitions (see Fig. 5.8-(e)) as it allows for effortless transitions (see Fig. 7.7-(d)). In our

study, 8 participants in the Desktop and 6 in the VR reported that Unified lowered mental demand. One participant commented, "I don't need to memorize much, as I don't need to spend more time on transitions (P4)." Our findings partially align with previous studies [136], exploring how frequent information checking can impact mental load.

**Unified potentially better-supported workflow tracking.** We further observed that workflow tracking capability potentially adds additional burden to the mental load in the Separated (see Fig. 7.7-(a)). Tracking a workflow often involves identifying and recognizing previously encountered objects to reduce redundant processing [137]. Within interactive transitions, we observed that almost all participants could directly navigate to the target cell in Unified to sync after exploring their data artifacts. We believe this is because participants could facilitate spatial information by displaying data artifacts near the target cell—either to the left or right for Desktop, or in front of the cell for VR, as shown in Fig. 5.7-(b) and (d). In contrast, we observed that facilitating spatial information in a spatially disconnected environment was impracticable in Separated. This led to considerable time spent identifying target cells due to the need to adjust to a new workspace with sudden changes, making it harder to recall the cell's position and resulting in higher context-switching costs [6].

**VR and Separated promotes provenance, but no noticeable differences between workspace configurations in VR.** In data science, provenance refers to documenting data's origins, lineage, and processing history, ensuring its traceability and reliability [107]. Previous studies have indicated that performing data science tasks in immersive environments had the potential to improve provenance compared to Desktop [30]. We observed similar findings in the Separated, where participants deleted fewer data artifacts and kept more, as shown in Fig. 5.9-(c) and (d). We believe this is largely due to the larger display space, as the computational notebook and data artifacts were located in independent workspaces. Participant feedback confirmed this: "I think I didn't delete data because I have more space (P13)" in VR+Separated. Additionally, subjective ratings in VR showed that 11 participants, surprisingly, from both Separated and Unified, appreciated the large display space. This contrasts with the Desktop+Unified, where 11 participants expressed concerns about limited display space. We believe this is due to the large display space in immersive environments, which allows participants to interact with a larger amount of content, resulting in the keeping of more data artifacts.

**Trade-off between workspace configurations in Desktop.** While the Desktop+Unified enabled faster task completion and effective transitions, participants found difficulties

managing the workspace due to its limited workspace. We believe combining the computational notebook with the embedded workspace on Desktop restricts the available space, leading to a cluttered environment when numerous data artifacts are generated. Although panning allowed navigation to empty spaces, participants often struggled to optimize the layout within a restricted view, leading to concerns about space limitations and increased effort to organize for effective comparisons. One participant mentioned, "I need to put a lot of effort into managing the workspace to ensure all the data and notebooks are not occluded (P8)". In summary, on the Desktop, the Separated improved workspace management but increased mental load and had less effective transitions. In contrast, the Unified reduced mental load and enabled effective transitions but required more effort to manage the workspace effectively.

**Unified more suitable for VR.** Unlike the Desktop+Unified, the workspace limitations were not present in VR+Unified. We believe this is due to the large display space available in the immersive environment, which allows for greater freedom to create effective layouts for comparison [16, 30], further reducing the mental load compared to Desktop+Unified. Specifically, eleven participants praised the large display space; one noted, "I think it didn't matter to display all the contents and required less effort than the desktop (P19)." Furthermore, participants largely favored pull-in/out transitions over walk-in/out, as walking required significant body movement (nine) for frequent transitions. We also noted that excessive body movement can lead to higher mental demands, as participants are required to retrieve information during the longer transition periods caused by the additional physical movement [7]. In summary, VR+Unified (ICoN) demonstrated low-effort transitions with embodied direct manipulations, improved workspace management and provenance, enhanced workflow adherence, and maintained low mental and physical demands throughout data science tasks.

## 5.8 Conclusion

In this study, we introduce ICoN, a system designed to facilitate a seamless transition between computational notebooks and embodied data science tasks within a unified environment. While our study observed tradeoffs between workspace configurations in the Desktop environment, it confirmed that ICoN enhances the transition experiences between code, data transformation, and visualization. Furthermore, embodied interactions within ICoN facil-

itate efficient exploratory capabilities in the data science process. However, we observed that participants may struggle with managing the workspace when dealing with numerous data artifacts in complex data science tasks. This observation underscores the need for innovative interaction methods to better organize content within the established workflow. In summary, we believe ICoN illustrates an innovative immersive data science workspace by integrating spatial and embodied interactions in immersive environments, offering a novel approach to data analysis and exploration.

# Chapter 6

# Exploring Organizational Strategies in ICoN

## 6.1 Introduction

Computational notebooks are structured as a series of "cells" that integrate code, documentation, tags, and visualizations into a single document [1], streamlining complex data analysis tasks such as building analytical pipelines, debugging, and comparative analysis [1, 2]. This integration has introduced a new paradigm in data science, making them a popular choice among data analysts [13]. However, as data analysis grows in complexity, computational notebooks often expand in length, posing substantial challenges. In response, researchers have extensively explored various methods to address challenges within extensive computational notebooks [16, 45, 138, 139].

Notably, Immersive Computational Notebook (ICoN), a system designed to operate computational notebooks within an immersive environment [16], was developed to investigate whether virtual reality's spatial and embodied characteristics can mitigate navigation challenges arising in traditional desktop setups. They found that physical interactions, such as rotating one's head or walking, offer a more intuitive and effective navigation. Specifically, they adopted a horizontal half-cylindrical structure in their initial setup, as this has been identified as effective for navigating and managing digital content in immersive environments [33, 59, 60]. However, they noted that available space in the given structure becomes constrained, particularly when using hierarchical structures and depth cues, necessitating frequent workspace management. This challenge underscores the significant impact of the initial structure on the data analysis process in immersive space, as participants heavily relied on initial setups to develop their workflows. Although previous studies have suggested potential organizational strategies for ICoN, they have not explicitly addressed how to effec-

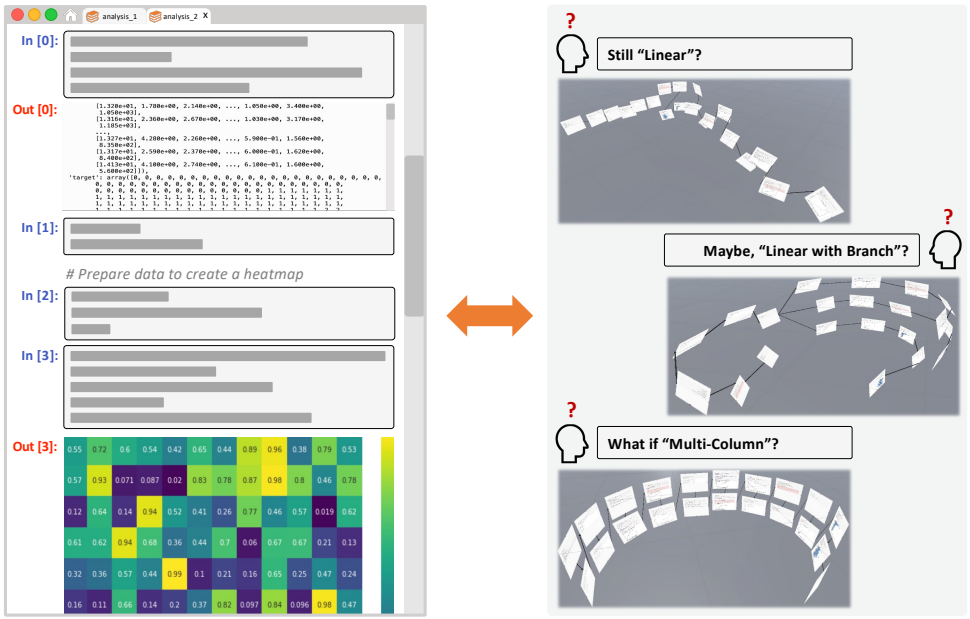



Figure 6.1: Cells are displayed linearly on a desktop computational notebook, resulting in a linear execution order (left). Users then wonder about the organizational strategies for using computational notebooks in an immersive environment (right).

tively arrange spatial elements to leverage ICoN's unique characteristics, such as execution order. Therefore, our first goal is to identify spatial structures within ICoN, to deepen our understanding of how computational notebooks are organized in immersive spaces.

The placement of cells plays a significant role in the use of computational notebooks, as this placement indicates the execution order [22]. In traditional computational notebooks, the execution order is generally represented linearly, top-to-bottom [22]. However, this linear representation further complicates data analysis, as real-world tasks often require non-linear comparative analysis [140]. Previous studies have explored non-linear execution orders in desktop setups [44, 67, 141]; however, fully utilizing non-linearity on the limited workspace of desktop screens required extensive navigation. As a result, a considerable amount of analysts continued to favor a linear representation [67]. However, it is not clear whether these observations can be generalized to the ICoN or how the potential of immersive spaces might enable analysts to encode meaning into their environments, such as the utilization of extra space observed in the "Immersive Space to Think" studies [50, 82]. Thus, our second goal is to investigate how various execution orders can be visualized in an immersive space and how the larger display space enables participants to engage more in non-linear analysis

compared to traditional desktop setups.

To systematically investigate our proposed goals, we conducted an exploratory user study under two conditions to capture a broader range of organizational strategies: the "Simple" condition, which involved fewer code cells to mimic basic data analysis tasks, and the "Complex" condition, with more code cells representing complex data analysis tasks. We presented participants with a random order of cells, intentionally forming no specific shape to avoid bias in building their workflow based on the initial setup. To effectively focus on the organizational strategies, we provided executed codes that included visual outputs or data previews. Participants were tasked with organizing the cells in a manner that made sense to them. Our results indicated a preference for half-cylindrical layouts, although quarter-cylindrical layouts were considerably adopted. Notably, participants performed more for non-linear analysis compared to traditional desktop setups [67].

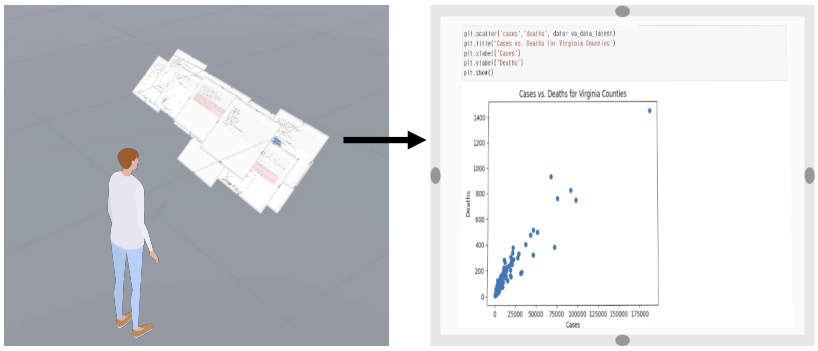
## 6.2 User Study and Evaluation

To systematically address our goals, we designed and conducted an exploratory study. Our primary objective was to explore organizational strategies for computational notebooks within an immersive environment where the execution order plays a significant role. We examined these strategies under two conditions: Simple and Complex. This section details our design rationale and process, providing comprehensive information on our methodology.

### 6.2.1 Research Questions & Goals

Our study aimed to address four research questions regarding spatial structures, execution order, space management strategies, and the observation as the number of code cells increased for computational notebooks within an immersive environment.

**RQ1. What are the spatial structures for managing and organizing computational notebooks in immersive spaces?** We aim to identify employed spatial structures within immersive computational notebooks. We are also interested in determining the most preferred structures.




(a) Initial setup (b) Cell design

Figure 6.2: Illustration of the experimental setup. (a) Cells are stacked in random order. (b) A closer look at the design of the cell, where codes and outputs are located at the center. Four holes on the side are available for visualizing the execution order.

**RQ2. What are the employed execution orders in ICoN, and how do they differ from 2D computational notebooks?** Cell placements play a critical role in the computational notebooks as this indicates the execution order. We aim to explore how execution orders can be visualized in an immersive space and deepen our understanding by comparing them with those in 2D computational notebooks.

**RQ3. What are space management strategies in the use of ICoN?** We aim to explore how participants utilize immersive space in the process of sensemaking activities within an immersive computational notebook, such as understanding and organizing code cells.

**RQ4. How does the number of code cells impact space management and interactions?** We have noted that the effort required for workspace management is increasing dramatically as the data science workflow becomes more complex. Thus, we aim to explore how the number of code cells affects content management within the immersive space.

### 6.2.2 Experimental Setup

Building on the methodologies used in exploring 2D computational notebooks, our study had participants work with pre-existing, non-executable code to focus on their organizational strategies rather than their programming skills. We took a screenshot of the entire Jupyter Notebook document, divided it based on each cell, and placed these cells within the immersive space. To enhance interaction and distinguish one cell from another, we displayed

the captured cells in windows that clearly defined their boundaries, as shown in Fig. 6.2-(b). These windows included additional features that allowed participants to link cells and visually represent the execution order. To establish these links, participants could pinch to grab one of four holes (top, bottom, left, or right) displayed on the windows and drag it to holes on other windows. Furthermore, participants were able to move and resize all provided windows.

The study was conducted with the Meta Quest 2 headset, providing a resolution of 1800 × 1920. This headset was linked to a PC with an Intel i7-11800H processor operating at 2.30 GHz and an NVIDIA GeForce RTX 3070 graphics card. The Meta Air Link feature facilitated a cable-free experience, leveraging the PC's computation power while the headset managed the rendering. This configuration allowed participants to navigate a $16m^2$ space freely. Initially, participants were placed in the center of this space, in front of a pile of cells (see Fig. 6.2-(a)), each measuring $0.35x0.30m^2$, at a distance of $1m$ from them.

### 6.2.3 Data

We conducted the study under two conditions to deepen our understanding of the use of computational notebooks differentiated by the number of code cells, **Simple** and **Complex**. To determine the appropriate number of code cells for the **Simple**, we used the same quantities employed in similar studies [16, 36]. For **Complex**, we considered various configurations. We concluded that providing an excessive number of code cells (e.g., 30-40 code cells) would make the task too challenging, leading us to double the number of code cells used in previous studies to better manage the complexity. Thus, the study featured with differing numbers of code cells provided in each condition as follows:

**Simple**. Ten code cells were provided, each employing the K-Nearest Neighbors (KNN) classification algorithm to analyze the "iris" dataset. This dataset was loaded from the official scikit-learn [65] documentation, and data visualization was conducted using matplotlib [120] libraries. The visualization included two different charts for the iris dataset, each presenting the same data but created by different parameter values. Two parameters within the KNN methods were manipulated to determine the optimal parameter combinations.

**Complex**. Twenty code cells were provided, focusing on the COVID-19 dataset for Virginia and two counties. Participants were not required to have prior knowledge of Virginia.

The dataset included three charts (e.g., scatter, bar, and line), each presenting the same data but analyzed differently. Conversely, each of the two counties was analyzed using the same methods but with their respective data, resulting in three graphs per county.

### 6.2.4 Participants

We recruited 20 participants (17 male, 3 female, ages 18 to 35) from a university mailing list, selecting individuals based on their familiarity with data science, machine learning algorithms, and experience with computational notebooks (e.g., Jupyter Notebook). Regarding VR experience, 12 participants reported having used VR, while the remaining indicated no prior experience with VR technology. Three of the 12 participants used VR weekly, and the remaining nine did not. All participants had either normal vision or vision corrected to normal.

### 6.2.5 Procedure

Our user study followed a full-factorial within-subjects design, with conditions balanced using a Latin square (2 groups). The study, on average, took less than two hours. Participants were initially welcomed and reviewed a consent form. Then, we briefly introduced the study's objectives and procedural steps. Following this introduction, participants proceeded to the various steps of the study as follows:

**Preparation.** We ensured that all participants had properly adjusted their Quest 2 headsets. This step was essential to ensure that each participant was in comfortable conditions and could clearly see the text.

**Training.** We began the training session by standardizing the terminology used in computational notebooks to avoid varying interpretations. The training was provided only once for the entire study due to the consistent operational logic across conditions, which differed only in the number of code cells. During training, participants watched demonstration videos and replicated specific tasks within a VR environment. They also had the opportunity to ask questions about operations or tasks. Recognizing the unique challenges of the VR setting, we extended the training sessions to give participants sufficient time to become familiar with the immersive environment. This approach helped address potential VR-related issues such as

physical discomfort and learning curves. The training concluded once participants achieved proficiency in the tasks and operations, which generally took 10-15 minutes.

**Study Task.** After completing the training session, participants moved on to the study task. We provided a context for each task, including brief explanations of the algorithms, data, and specific tasks they were required to complete. Specifically, we informed that the goal is to provide guidance for new team members, enabling them to understand not only the analysis results but also the processes underlying these findings. Additionally, we advised that the arrangement should facilitate collaboration and further development of data analysis. To complete the given task, participants were required to reorder and link the cells in a way that made sense to them. Although a "correct" order existed, participants were not required to organize the notebooks correctly to complete the task. This approach was chosen to prevent participants from hesitating or feeling pressured to find the correct answer. Participants were not constrained by time limits for completing the tasks but were encouraged to focus on accuracy and efficiency. Furthermore, we re-positioned participants at the center of the room and oriented them in the same initial direction before starting each task to ensure consistency.

**Questionnaires.** After each condition, participants completed a Likert-scale survey, adapted from the System Usability Scale (SUS) and NASA Task Load Index (TLX), to document their subjective experiences. Additionally, they provided qualitative feedback on the advantages and disadvantages of the condition they had just interacted with. The study concluded once participants had successfully completed the questionnaires for all conditions.

### 6.2.6 Measures

In our study, we recorded the participants' entire procedures to delineate their organizational strategies. This method allowed us to analyze not only the final layout strategies but also the intermediate steps participants took to build their final arrangements. Such an approach offers deeper insights into how participants utilize the immersive space.

In addition to recording participants' processes, we collected a survey using a 7-point Likert scale to assess their subjective experiences. Additionally, we conducted semi-structured interviews to gain deeper insights into each condition that identified experiences and areas to be improved.




Figure 6.3: Implemented spatial arrangements. (a) Participants were fully surrounded by code cells, forming a complete cylindrical layout, whereas (b) Cells were arranged in a half-cylindrical layout, providing free space behind the participants. (c) Cells were set up only in front of the participants but still in a curved formation, forming a quarter of a cylindrical layout. (d) Cells were placed in a flat wall shape only found in the **Simple**.

Following their interaction with each condition, we collected quantitative data through specific metrics to answer our research question. *Number of moving cells:* we recorded the total interactions involving the movement of cells for organizational purposes. *Number of add/delete links:* we counted whenever links were added or removed to indicate execution order. *Number of participants began with rearranging initial setups:* considering the initial setup's piled-up cells, we expected that participants might need to rearrange them into other structures to make codes visible. Therefore, we counted the participants who began arranging the codes before organizing them into a designated order.

## 6.3 Results & Discussions

This section discusses our results, and the following discussion addresses our research questions. To address RQ1, we explored how participants utilized spatial structures based on their final layout in each condition. For RQ2, we analyzed the execution order and flow employed in their final structures. Furthermore, to deepen our understanding, we compared our findings with those from a previous study on 2D computational notebooks [67], specifically focusing on non-linear analysis engagement. For RQ3, we analyzed recorded videos to observe participants' processes in achieving their final structures, specifically to understand how they utilized the immersive space. For RQ4, we analyzed quantitative measurements, subjective ratings, and feedback from post-condition interviews. All final structures are included in the supplementary material.

**Exploring spatial structures in ICoN.** In our study, participants were required to organize their computational notebooks in a way that made sense to them. We analyzed their final structures to understand the functional implications of their spatial structures. Our study identified four primary spatial structures adopted by users: full-cylindrical, half-cylindrical, quarter-cylindrical, and planar, as illustrated in Fig. 6.3. We defined full-cylindrical structures when participants were fully surrounded by cells. Half-cylindrical structures were identified when participants arranged cells to leave free space behind them. Quarter-cylindrical structures were recognized when participants formed a curved cylindrical structure but left empty spaces on the back, left, and right sides. Lastly, planar structures were considered when cells were displayed in a flat wall shape without any curvature. We observed that the majority of participants chose half-cylindrical structures, with 50% in Simple and 45% in Complex. Quarter-cylindrical structures were the second most popular, selected by 30% of participants in both conditions. While half and quarter-cylindrical structures were consistently used across conditions, other structures varied: 15% of participants in Simple adopted full-cylindrical structures, and the planar structure was the least utilized, with only 5%. However, with Complex, observation shifted: 25% of participants opted for full-cylindrical structures, and notably, no participants chose planar structures in an immersive space (see Table 6.1).

Our findings, which observed that participants predominantly chose half-cylindrical structures and rarely selected planar structures for organizing computational notebooks in immersive spaces, are consistent with previous studies [33, 59, 60]. Thus, we suggest adopting half-cylindrical structures for computational notebooks in immersive environments, while quarter-cylindrical structures should also be considered for more complex data analysis scenarios. However, we believe these observations are attributed to similarities in engaging with small multiples and employing physical interactions in immersive environments [34]. Therefore, future research should investigate alternative interaction methods, such as grabbing objects from a distance, to further generalize and validate these observations.

**Employed execution order in ICoN.** Across both conditions, our study identified five primary execution orders that were adopted by users: linear, multi-row, multi-column, linear with branch, and diverse, as illustrated in Fig. 6.4. We defined a linear execution order as being laid out in a single direction, either left-to-right, top-to-bottom, or in the reverse direction. However, a non-linear execution order was defined when multiple directions were employed or directions were split into different paths. A multi-row execution order was

| Spatial Structures | | Number of Participants | |
|---|---|---|---|
| | | smaller | larger |
| Cylindrical | Full | 3 (15%) | 5 (25%) |
| | Half | 10 (50%) | 9 (45%) |
| | Quarter | 6 (30%) | 6 (30%) |
| Planar | | 1 (5%) | 0 (0%) |

Table 6.1: Distribution by spatial structures in ICoN.

defined when changes in execution order created additional rows, while a multi-column execution order was identified when changes created additional columns. In addition, we defined linear with branch where multiple changes in execution order were made from a single cell. Lastly, we categorized an execution order as diverse when participants employed more than two types of execution orders.

While only 20% in Simple and 15% in Complex utilized linear execution order, a majority of participants–80% in Simple and 95% in Complex–chose non-linear execution order. This non-linearity included linear with branch, multi-row, multi-column, and diverse execution order (refer to Table 6.2 for details). Notably, we observed that the use of non-linear execution order has dramatically increased—approximately 30%–compared to those found in desktop setups when exploring 2D computational notebooks [67]. We believe this shift is due to the infinite display space provided by VR, which likely encourages participants to organize computational notebooks in ways that more closely reflect real-world analysis, leading them to engage more in non-linear analysis. Consequently, we posit that immersive spaces allow users to build and organize data analysis workflows in more intuitive and logical ways.

**Space management strategies in the process of organizing computational notebook.** In the process of organizing computational notebooks, we observed that the majority of participants (75%, 15 out of 20) divided the given space for specific purposes, using it as presentation and scratch spaces, as shown in Fig. 6.5. In the presentation space, participants displayed their final structures with deliberately arranged execution orders, indicating that this area is for refining presentations and reports derived from their analyses. By isolating this space from others, participants were able to focus more effectively on organizing their final structures. In the scratch space, which served as a temporary holding area, participants placed code snippets that were not in sequenced order. Utilizing this space enabled participants to keep code snippets accessible for review and integration at a later stage.

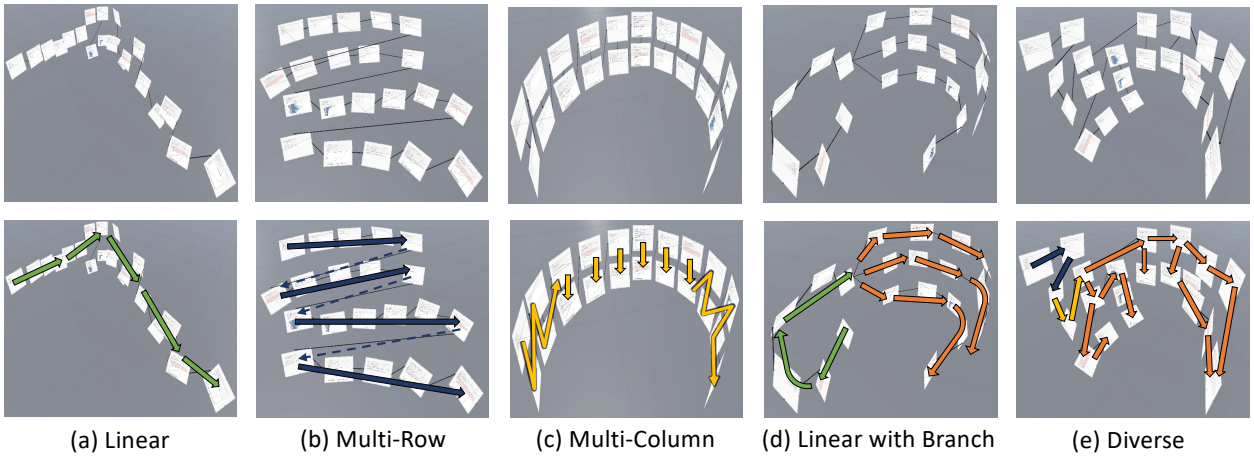



Figure 6.4: Illustration of execution order (top) and clarification of corresponding order (bottom). (a) Cells followed linear execution order. (b) Cells formed multiple rows, whereas (c) cells were set up in multiple columns. (d) Cells initially followed a linear order but switched to a branching strategy to facilitate code comparison. (e) Cells involved multiple execution orders simultaneously; for instance, Multi-Row, Column, and Branch were used together.

| Execution Order | Number of Participants | |
|---|---|---|
| | smaller | larger |
| Linear | 4 (20%) | 1 (5%) |
| Multi-Row | 0 (0%) | 1 (5%) |
| Multi-Column | 1 (5%) | 2 (10%) |
| Linear with Branch | 14 (70%) | 12 (60%) |
| Diverse | 1 (5%) | 4 (20%) |

Table 6.2: Distribution of execution order in ICoN.

More specifically, within the scratch space, participants further divided this area for various purposes. 60% of participants (9 out of 15) grouped similar codes with corresponding visualizations, while 40% (6 out of 15) organized code cells and visualizations separately. We believe this separation of code-intensive tasks from visualization enabled participants to establish a logical order more efficiently, as a participant highlighted, "clustering code cells enable comparative analysis easier (P7).".

**Impacts on analysis process and space management as the number of codes increased.** Although the number of code cells did not lead to distinct differences in organizational strategies, it shows the notable impact on the analysis process and space management strategies. In our tested task, participants frequently needed to revisit cells. Notably, iden-

tifying revisited cells became more challenging in Complex; however, we did not observe similar observations in the Simple. We believe that the benefits of spatial information in boosting memory capabilities [7, 102, 112] are diminished when participants interact with a larger number of code cells. This was partially confirmed in our study, where 11 participants noted challenges; for example, one commented, "Identifying specific cells was challenging as I needed to recall many cells (P6)."

Challenges further arose as the number of code cells increased. In the initial stage of the task, many cells were not visible as they were piled up, prompting nearly all participants (90%, 18 out of 20) to start rearranging the computational notebook in Simple to better understand the codes. However, this observation diminished as the number of code cells increased, with 65% (13 out of 20 participants) engaging in rearranging in Complex. Consequently, they began organizing the codes into the final structure without a comprehensive understanding of the given codes. To further understand this observation, we analyzed participants' interactions with moving cells. On average, participants who started by rearranging cells interacted an average of 49 times and an average of 31 times for those who did not rearrange in Simple. However, this observation shifted in Complex: those who started by rearranging cells had an average of 148 interactions; however, this number dramatically increased with those who did not rearrange cells by 45% to an average of 215 interactions. We believe that participants were hesitant to rearrange due to the increased effort required. Although they believed this approach would require less effort, it ultimately led to more effort and made it harder for them to complete the task. This observation is confirmed by our qualitative ratings of "hard to complete the task", with an average score of 4.43 for those who did not arrange first, slightly higher than the score of 3.77 for those who arranged initially. In summary, we noted that as the number of codes increases, organizations' assistants are required to fully utilize the identified benefits of spatial memory and effectively manage the workspace.

## 6.4 Conclusion

In this study, we aim to deepen our understanding of the spatial structures employed for computational notebooks in immersive spaces and examine how various execution orders can be visualized in an immersive context compared to desktop setups. Our findings indicate that the half-cylindrical layout is predominantly used, and a linear with branching execution

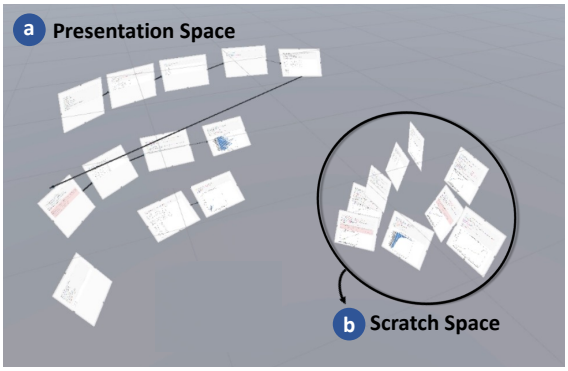



Figure 6.5: Illustration of space management strategies within ICoN. (a) participants organized the cells in a structured manner, whereas in (b), the placement of cells appeared less organized.

order was mostly chosen by participants as it facilitates easier results comparison. Notably, we observed a significant increase in the adoption of non-linear analysis in ICoN compared to desktop setups. This observation underscores the potential of computational notebooks in immersive spaces to encourage analysts to engage more in non-linear analysis. Given the frequent need for comparative analysis in real-world scenarios, we believe that ICoN provides an environment where analysts can more logically and easily construct their workflows. However, the employed interaction methodologies required participants to manually move individual code cells when they wanted to modify their organization. As a result, participants reported that additional assistance might be necessary to effectively organize code cells when working with larger quantities.

# Chapter 7

# Embodied Content Organization for ICoN

## 7.1 Introduction

With the rapid development of immersive technologies, immersive analytics has shown great potential to enhance the data analysis process [3, 4, 83]. Notably, immersive computational notebooks extend the traditional computational notebooks into immersive environments [16], which enables users to work within spatially organized, interactive workspaces, offering a new paradigm in data science. However, as analysis gets more complex, immersive computational notebooks present significant challenges, particularly with scalability.

One of the key benefits of immersive computational notebooks is the greater flexibility they offer in organizing artifacts through embodied interactions [142]. Specifically, analysts can adjust execution order and cell placement—transforming linear sequences into non-linear layouts (local) and repositioning cell groups (global)—to support efficient navigation. However, as the number of cells increases, organizing content in immersive environments becomes increasingly effort-intensive [111, 143, 144]. Unlike prior work on organizing documents in immersive spaces [145], immersive notebooks introduce an additional proxy to manage: execution indicators. For instance, analysts must manually interact with spatially distributed cells and their associated execution indicators one by one. As a result, maintaining "well-organized" structures that clearly reflect analysts' intentions and support efficient navigation within the workspace becomes significantly challenging [22, 114].

Common practices for reducing the effort required to build well-organized structures can be observed in a desktop setup, particularly when using organizational guidance. Organizational guidance has proven effective in 2D desktop environments such as Miro [43] and Figma [42], where users can quickly initiate structured workflows using pre-defined visual layouts. This

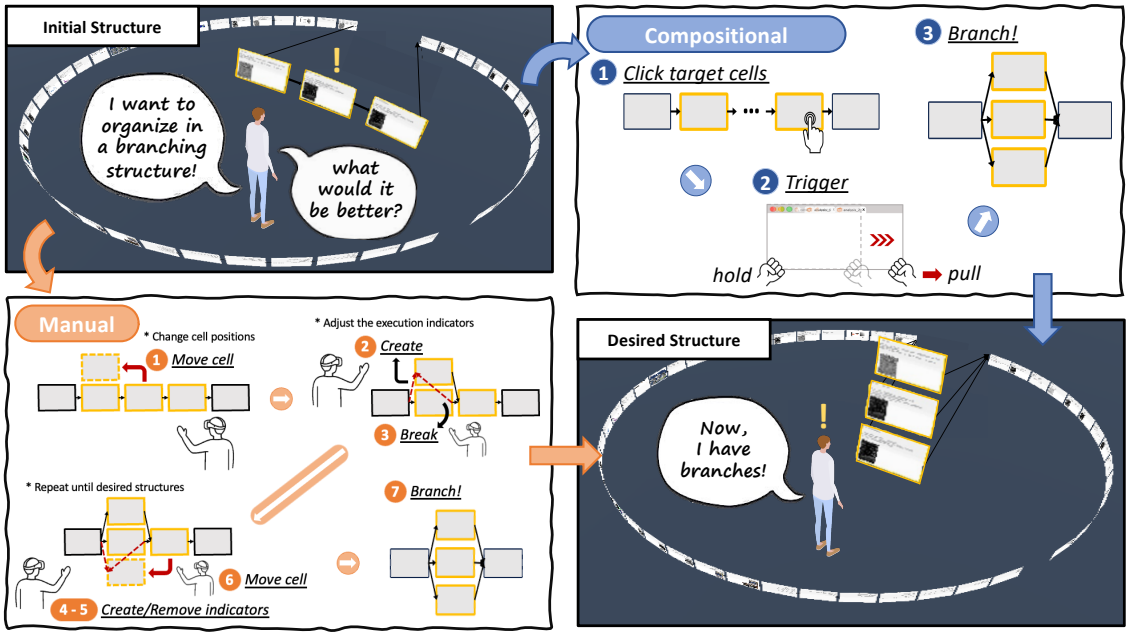



Figure 7.1: Cells are displayed linearly on a desktop computational notebook, resulting in a linear execution order (left). Users then wonder about the organization's strategies for using computational notebooks in an immersive environment (right).

guidance not only reduces the time and effort required to set up analysis but also helps maintain clarity and consistency throughout the process [37]. Moreover, guidance has been shown to support scalability by offering reusable structures that simplify the organization of large analytical workspaces and reduce repetitive manual adjustments [146]. **Building on this, our primary goal is to reduce the effort required to build well-organized structures within large-scale immersive computational notebooks by utilizing organizational guidance.**

While organizational guidance shows promise in reducing user effort, it also presents unique challenges when applied to immersive computational notebooks. Current immersive notebooks use natural body movements to support more intuitive and engaging workflows. While traditional WIMP (Window, Icon, Menu, Pointer) interfaces are effective for managing multiple commands in a 2D space [147], their use in immersive environments can disrupt the sense of immersion, as analysts must frequently shift their attention between spatial menus and target artifacts [30]. To address this, we adopted embodied interaction to trigger organizational guidance, aiming to maintain user engagement and enhance the intuitiveness. We also believe embodied interaction enables a seamless experience between the triggering

mechanism and manual manipulations, as both rely on the same interaction modality. Additionally, immersive environments introduce an additional dimension—depth, which allows analysts to highlight or lower the priorities [148, 149]. Therefore, the design of organizational guidance should also integrate spatial cues across all three dimensions: horizontal, vertical, and depth-based structures.

To this end, our work introduces organizational guidance for immersive computational notebooks. We provide a set of structures, each parameterized by three key properties: execution order, layout, and analysis phase. Specifically, the organizational guidance includes a total of 10 unique structures: five focused on execution logics, two for narrative-focused, and three supporting both execution logics and narrative-focused. Furthermore, we supported flexible adjustments within guided structures, such as merging layouts, adjusting orientation and dimensions, and toggling execution indicators, enabling the guidance system to adapt content organization to users' needs.

Our guidance system also supports users in grabbing and moving large-sized proxies, such as groups of cells. However, analysts may struggle to precisely position these large structures within compact spaces. Furthermore, analysts may become overly reliant on organizational guidance, which can diminish their engagement in analytical reasoning and decision-making processes. As such, in addition to our primary goal of reducing interaction effort, we were also interested in exploring the potential trade-offs introduced by the use of organizational guidance. To examine these trade-offs, we designed the computational notebooks used in the study to include a variety of structures, such as long linear sequences and nested branches (e.g., branch-over-branch), which resulted in large cell groupings. Therefore, to systematically investigate our proposed goals, we conducted a user study comparing workspace structuring with and without organizational guidance in immersive computational notebooks. Our findings revealed that organizational guidance enabled participants to build structures rapidly and with significantly less effort. Additionally, participants were willing to revise their structures as their analysis progressed, demonstrating the system's support for dynamic reorganization. While we identified areas for improvement—particularly in the use of the depth dimension—participants expressed that the guidance covered most of the coding logic present in the notebooks.

In summary, our main contributions are:

- We designed and implemented an organizational guidance system for immersive com-

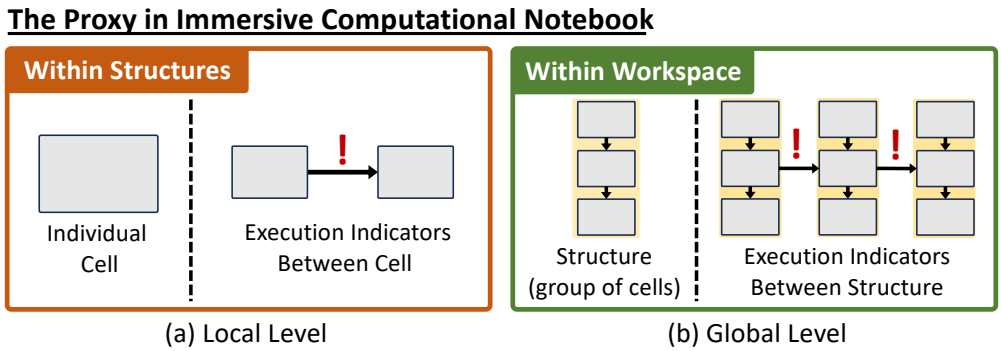



Figure 7.2: The type proxies used to organize the immersive computational notebooks.

putational notebooks, a research prototype that aims to reduce the effort required to build a well-organized structure for large-scale analysis.

- We conducted a user study comparing workspace structuring with and without organizational guidance to empirically investigate the effects of organizational guidance.

## 7.2 Design Rationale

Our goal is to provide system-level support for content organization within flow-based systems in immersive environments. In a flow system, users interact with various spatial proxies at different levels of granularity [16, 130]. At the local level, they adjust connections and reposition individual artifacts to refine the flow. At the global level, they manage groups of artifacts, repositioning clusters and modifying higher-level flows. In immersive computational notebooks, this translates to adjusting execution logic and positioning individual cells at the *local level* (see Fig. 7.2-(a)), and repositioning entire structures and their interconnections at the *global level* (see Fig. 7.2-(b)). However, as the number of proxies increases, the effort required to maintain an organized structure that accurately reflects analytical reasoning grows significantly [142]. To address this challenge, the following sections present our design goals and framework, which aim to support efficient content organization through both local and global-level refinements.

### 7.2.1 Design Goal

**G1. Support well-organized structures for exploratory analysis and storytelling (local-level).** Computational notebooks support a wide range of tasks—from exploratory data analysis to storytelling for communicating results [150]. During exploratory analysis, analysts often build structures where the execution logic is clearly conveyed [2]. In contrast, storytelling prioritizes visual narratives over the execution logic within the structures [22]. To comprehensively support the wide range of computational notebooks' uses, the system should accommodate various forms of well-organized structures, some that clearly convey execution logic, and others that effectively communicate visual narratives.

**G2. Ensure a spatially connected and intuitive triggering mechanism (local-level).** In immersive environments, users often use embodied interaction, allowing them to engage with content through natural body movements and enabling a fluid, spatially connected experience [51, 151]. This form of interaction also extends to triggering mechanisms, where gestures serve as a fundamental input modality for executing operations. Prior research has shown that gestures can offer an intuitive and efficient way to invoke system functions. Building on this foundation, our goal is to design a triggering mechanism that leverages embodied interaction.

**G3. Support human intervention within the composite structure (local level).** Data analysis is inherently dynamic; analysts explore multiple hypotheses, revisit earlier steps, and adapt their approach in response to new insights or unexpected outcomes [10]. As their understanding of the data deepens, their reasoning process evolves—prompting changes in how they organize, prioritize, and structure their notebooks. While compositional structuring may offer a faster way to initiate the analysis, it can become limiting when analysts want to make refinements, such as fine-tuning or deviating from the composited structure. Therefore, the system should allow users to easily override, adapt, or refine the composited structures.

**G4. Support effective global-level organizations.** After completing local-level organization, analysts often proceeded to global-level adjustments, such as relocating entire structural groups to different areas of the workspace. However, as the number of cells increases and the workspace expands, such adjustments require moving across large spaces and restructuring composite structures in new locations, resulting in a time-consuming and effort-intensive process [142]. Therefore, systems should also enable users to move entire

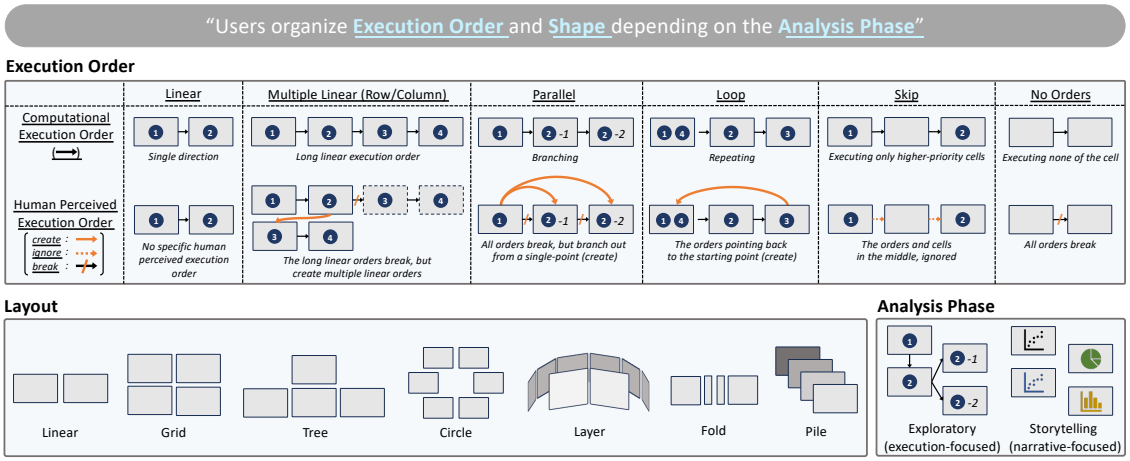



Figure 7.3: Design framework for embodied compositional structuring.

structures along with their associated execution indicators and cells at once.

### 7.2.2 Design Framework

While prior work in immersive environments has emphasized general layout principles [145], visual aesthetics alone are insufficient for immersive computational notebooks. Therefore, we identify three key design aspects based on a common pattern observed in how users organize immersive computational notebooks: "Users organize Execution Order and Layout depending on the Analysis Phase" (see Fig. 7.3). Below, we detail each of these three aspects.

**Execution Order.** We identified five execution orders employed in computational notebooks. Among the identified execution orders, we additionally found that they present two perspectives: the computational execution order and the human-perceived execution order. The computational execution order reflects the system-enforced sequence in which code cells are executed, typically in a linear manner [10]. In contrast, the human-perceived execution order emerges from how analysts mentally organize their workflows [2]. Below, we detail how humans perceive differently from the computational execution orders. *Linear*: The most traditional pattern, especially in desktop settings like Jupyter Notebooks [12], where the human perceives the same as computational order. *Multiple Linear*: Analysts often organize linear sequences into multiple rows or columns to break the long linear computational orders [142]. *Parallel*: Common in complex analysis, humans create branching execution paths from a

single point, allowing multiple hypotheses or variations to be executed simultaneously [44]. *Loop*: Reflecting iterative analytical processes, analysts establish loops where the execution path circles back to prior steps [152]. *Skip*: To optimize performance, analysts selectively execute cells while skipping others, particularly computationally intensive operations or low-priority cells [153]. *No-Order*: Analysts may not execute any cells, but focus on spatial grouping, where the execution order is not the primary concern [154].

**Layout.** Prior research systematically studied the design space of organizations' strategies in immersive environments [16, 138, 145, 155, 156]. Building upon previous explorations, we identified seven layouts commonly employed when organizing artifacts in immersive settings: *Linear*: Artifacts are arranged sequentially in a single line. *Grid*: Artifacts are distributed across multiple rows and columns. *Tree*: Child artifacts diverge from a single parent node at the same hierarchical level. *Circle*: Artifacts are organized in a circular shape. *Layer*: Analysts create smaller layers by leveraging the depth by positioning artifacts closer to themselves, prioritizing important information. *Fold*: All artifacts are collapsed, allowing less critical information to be hidden. *Pile*: Artifacts are stacked, with the first element remaining visible to represent the group, which enables quick referencing while maintaining spatial compactness.

**Analysis Phase.** In computational notebooks, analysts primarily go through two phases: exploratory analysis and storytelling. Prior work in immersive analytics emphasizes that these phases require different organizational strategies to support exploratory analysis and storytelling [3]. *Exploratory analysis*: Analysts primarily focus on execution order to maintain logical consistency in their workflow [10]. *Storytelling*: Analysts prioritize highlighting key insights. Analysts group cells semantically, cluster outputs, and often ignore the execution flow to emphasize the narrative [22].

## 7.3 Embodied Compositional Structuring for Immersive Computational Notebooks

We introduce embodied compositional structuring, a prototype system designed to support users in building and organizing artifacts within the context of immersive computational notebooks using embodied interactions. Embodied compositional structuring consists of three main components: structures, triggering mechanisms, and additional interactions. Be-

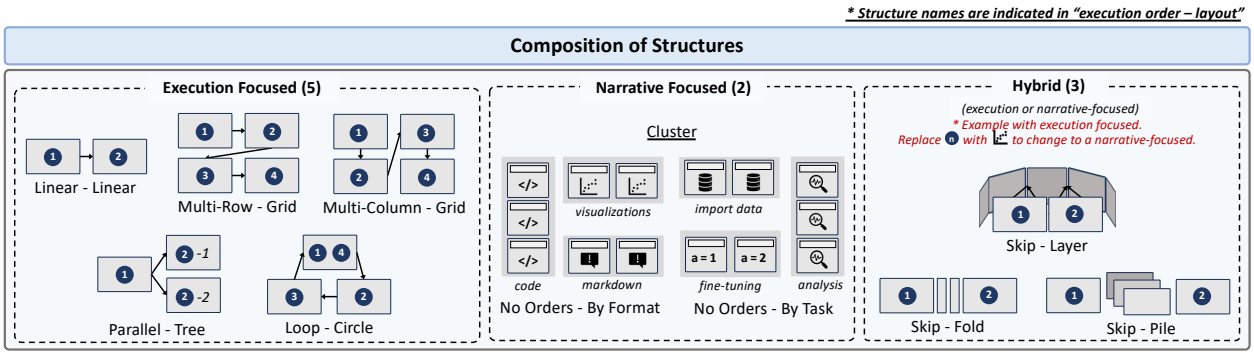



Figure 7.4: Composition of structures for embodied compositional structuring based on our design framework.

low, we describe each of these components in detail.

### 7.3.1 Structures

Users manually organize cells, often resulting in misaligned or inconsistent layouts [142]. In contrast, predefined structures provide a framework for constructing well-organized structures, aligning with our design goal (G1) of supporting clear structures for both exploratory reasoning and visual narrative at the local level. To this end, we support 10 unique predefined structures derived by execution orders, layout, and the analysis process discussed in the design framework in Sec. 7.2.2.

**Execution Focused (5).** In these structures, the primary focus is placed on maintaining coherent execution orders and supporting the underlying analytical workflows. 1) *Linear-Linear*: A single linear execution order arranged in a linear layout. 2) *Multi-Row-Grid*: Multiple linear execution orders organized into several rows, creating a grid layout. 3) *Multi-Column-Grid*: Multiple linear execution orders organized into several columns, creating a grid layout. 4) *Parallel-Tree*: Parallel execution orders that branch out independently from a single starting point, creating a tree layout. 5) *Loop-Circle*: An execution flow that forms a loop in a circular layout, supporting iterative or cyclic analysis processes.

**Narrative Focused (2).** In these structures, the primary focus is placed on organizing cells to highlight key insights and enhance the clarity of the analytical narrative, rather than strictly following execution order. 1) *Cluster-by-Cell Format*: Cells are clustered by their content format (e.g., code, visualization, text) to emphasize their functional roles. 2)

*Cluster-by-Task*: Cells are clustered according to distinct analytic tasks, highlighting high-level workflow structures.

**Hybrid (3).** In these structures, the organization supports both coherent execution paths and narrative clarity by selectively skipping or reshaping parts of the workflow to balance analytical flow and storytelling. 1) *Skip-Layer*: Skips parts of the workflow by pulling specific cells closer in depth, creating a layered structure across different spatial levels. 2) *Skip-Fold*: Skips parts of the workflow by folding sequences, compressing the structure while preserving logical order. 3) *Skip-Pile*: Skips parts of the workflow by piling cells on top of each other, forming a stacked structure that allows flexible access across steps.

### 7.3.2 Triggering mechanism

Our goal was to ensure that transforming target cells into the provided structures maintains immersion and does not disrupt the user's spatial experience. During the design process, we considered employing the WIMP (Window, Icon, Menu, Pointer) interaction, where users interact through buttons embedded within the menu interface. However, WIMP introduces substantial context-switching costs, requiring users to alternate their attention between target cells and menu [30]. Additionally, to accommodate the wide range of provided structures, numerous buttons had to be introduced. However, fitting them all into a single menu either results in an oversized interface that reduces usability, or forces smaller buttons that introduce precision challenges in immersive environments [157]. In contrast, embodied interaction enables seamless transitions between target proxies (i.e., cells) and intended actions [6]. This approach fosters more natural, aligning with our design goal (G2) of promoting fluid, engagement-driven interaction. Therefore, we adopted embodied interaction, allowing users to remain focused on the organization without being distracted by external commands. In the following sections, we describe how users can trigger our provided structures (see Fig. 7.5).

**With the Proxy Window.** In this interaction, all actions involved a "grab" gesture. To enhance the sense of physically grasping an object, we provided visual feedback, the Proxy Window, which provides feedback to help users stay aware of their actions. Through the pilot study, we identified that it reduces errors and improves the reliability of interaction. The Proxy Window appears near the user's hand when cells are selected (see 1 in Fig. 7.5) and supports structure creation through the following gestures:

- Linear-Linear (❹ ➡ ❶): after selecting cells, users grab&pull the Proxy Window outward using both hands, imagining they are stretching the cells. The selected cells would then be organized in a linear execution order and displayed in a linear layout.

- Multi-Linear-Grid (❷-1. ➡ ❸-1.): After selecting the cells, users grab the Proxy Window and move their hands diagonally, imagining the first cell positioned at the top and the last at the bottom. The selected cells are then organized in a multiple-row execution order (the default option) and displayed in a grid layout; switching to a multiple-column execution order requires adjusting the grid's orientation.

- Parallel-Tree (❷-2. ➡ ❸-2.): Users selecting only the first cells of each branch. They then grab&pull the Proxy Window outward with one hand, imagining the cells branching out from a single cell. The selected cells are organized in a parallel execution order and displayed in a branching, tree layout.

- Loop-Circle (❷-3. ➡ ❸-3.): After selecting the cells, users grab the Proxy Window and move both hands in a circular motion, imagining cells into a continuous loop. The selected cells are then organized in a looped execution order and displayed in a circular layout.

- Skip-Fold (❷-4. ➡ ❸-4.): After selecting the cells, users grab the Proxy Window and squeeze with both hands, imagining squeezing all the cells. The selected cells are organized in a skip execution order and displayed in a folded layout.

- Skip-Pile (❷-5. ➡ ❸-5.): After selecting the cells, users grab the Proxy Window and squeeze with one hand, imagining piling the cells on top of one another. The selected cells are organized in a skip execution order and displayed in a stacked, piled layout.

**Without the Proxy Window.** For specific interactions, a Proxy Window was unnecessary, as these gestures were clearly distinguishable from others and did not require "grab" actions.

- Skip-Layer (❷-6. ➡ ❸-6. and ❹ ➡ ❶): After selecting an individual cell or an entire structure, users perform a Follow-Me gesture by pulling cells closer to themselves or a Go-Away gesture by pushing them back to their original positions, adjusting the depth placement of the cells in space.

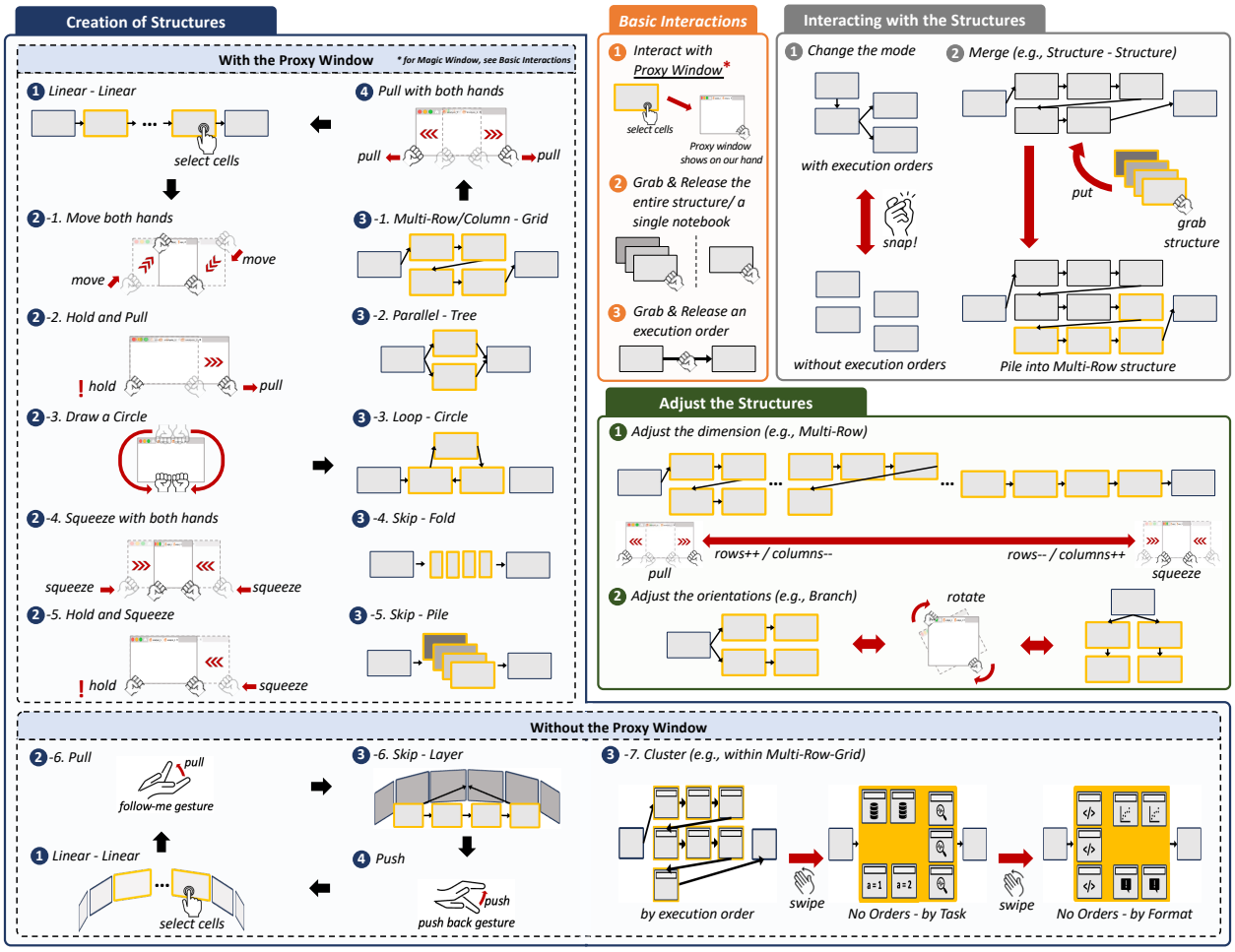



Figure 7.5: Illustrations of gesture-based interactions used to trigger provided structures and interact with the embodied compositional structuring.

- No-Orders-Cluster (3-7.): Users place their hands near the existing structure and perform a swipe gesture to cluster the cells by format or task. Each swipe changes the clustering mode.

### 7.3.3 Additional interaction with the structures

To support evolving analytical workflows, we introduced an additional interaction design for both local and global-level organizations. These interactions support both the global-level organizations and the efficient refinement of existing ones, which aligns with our goals of supporting human-in-the-loop structuring (G3) and facilitating effective global-level organization (G4). Below, we outline how the additional interactions can be performed.

2**-(left) Move along with group of cells.** Once users organize cells using the provided structures, a grabber appears at the center of the structure, but only when users approach and place their hands near it, to minimize occlusion. Users can then grab the structure through the grabber, move it freely, and release it at the desired position.

2**-(right)/**3 **Grab single cell/execution indicator.** Within the system, users can grab individual cells or execution indicators. In existing structures, grabbing a single cell and releasing it away from the structure removes the cell, while releasing it back into the structure updates the structure to include it. Additionally, users can grab execution indicators generated by the system and reposition them to adjust the execution order to better reflect the user's intentions.

1 **Change mode.** Users can toggle the visibility of the execution indicator based on their analytical needs. The indicator appears/disappears when users select cells and perform a snapping action.

2 **Merge.** Users can grab one structure and release it into another existing structure. The inserted structure is then transformed into the same format as the target structure.

1 **Adjust the dimensions.** For a Multiple-Row/Column-Grid structure, users can adjust the number of rows or columns by squeezing or unsqueezing the Proxy Window after selecting cells in a structure. Squeezing decreases the number of rows or columns, while unsqueezing increases them.

2 **Adjust the orientations.** Users can change the orientation of Multiple-Row/Column-

Grid and Parallel-Tree structures to either a horizontal or vertical manner by selecting cells and rotating the Proxy Window.

## 7.4 User Study

We compare embodied compositional structuring, where the system assists participants in building structures, with manual structuring, where participants must interact with individual artifacts one by one. Furthermore, to effectively evaluate the impact of embodied compositional structuring, we simulated a large-scale analysis scenario in which users were required to interact with a substantial number of artifacts. In summary, we address the following three research questions:

- **RQ1. Does embodied compositional structuring help analysts organize more quickly and with less effort?** We aim to determine whether embodied compositional structuring enables users to build structures more quickly and with minimal effort.
- **RQ2. Do users continue to abandon organizational refinement even when using embodied compositional structuring?** As the number of artifacts increases, users frequently abandon organizational refinements when interacting with them one by one manually [142]. This often leads to a disorganized structure, including inconsistent spacing, misalignments, and poorly placed execution indicators. Therefore, we aim to compare the final organizations under each condition.
- **RQ3. Does embodied compositional structuring reduce the variation in organizational strategies compared to manual structuring?** In system-level supported environments—such as LLM-based recommendation tools—users often rely heavily on the system's suggestions, leading to similar reasoning processes across individuals [158]. We anticipate that a similar pattern may emerge with embodied compositional structuring, where system-level support is introduced into the organization process. Therefore, we aim to compare the organizational strategies of manual and embodied compositional structuring.
- **RQ4. Are the provided triggering mechanisms practical and well-aligned with the user's intentions in building structures?** We designed gesture-based

triggering mechanisms by standardizing and adopting commonly perceived user behaviors identified in prior studies [145]. However, a mismatch may still arise between the provided mechanisms and users' intended actions, potentially leading participants to prefer manual structuring. Therefore, we aim to explore whether the provided gestures were perceived as both intuitive and practical in supporting the creation of structure.

### 7.4.1 Study Conditions and Data

To examine the effectiveness of embodied compositional structuring, we conducted the study under two conditions—Manual and Compositional, as follows:

- **Manual**: participants used traditional embodied interactions to organize the notebook, manually position cells, and adjust execution indicators to establish execution order.
- **Compositional**: Participants had access to the same fundamental interactions as in the Manual, but could additionally use gestural interactions to transform target cells into desired structures within the provided structures.

Regarding the data used in each condition, we explored multiple configurations. To clearly observe differences in organizational performance between the Manual and Compositional, we considered using a large number of cells. However, through a pilot study, we found that using too many cells (e.g., 75 or more) led to unreasonably long completion times. In contrast, using 50 code cells provided a reasonable balance, requiring a meaningful organizational effort while keeping the study duration manageable. In addition, the code used in the study was drawn from an introductory computer vision course, featuring various visual outputs and complex fine-tuning tasks, which aligned well with our goal of creating complex analytical scenarios. To help participants focus on organizational tasks rather than understanding the underlying code logic, we annotated specific cells to highlight unique structural patterns. The code used in the study is provided in the supplementary material.

### 7.4.2 Task

With the following study conditions and data, we structured three tasks to systematically address our research questions.

**Task 1: Identifying Execution Order** Participants began by reviewing the codes in a Jupyter Notebook on a desktop setup. They asked to identify non-linear execution order, such as branches and loops. This task involved interpreting the code to uncover how the analytical process was structured, allowing participants to focus solely on organizational aspects in the later tasks.

**Task 2: Reorganizing the Notebook in VR** Next, we informed that the notebook has been imported within an immersive environment using a circular layout, resulting in a huge ring shape. Participants were asked to reorganize the cells to create a more logical execution order and to construct a workspace that supported effective navigation. This included arranging cells in ways that reflected the analytical flow identified in Task 1 and clarifying the step-by-step reasoning process through spatial structuring.

**Task 3: Presenting and Communicating Results in VR** In the final phase, participants adjusted the notebook's structure to highlight key findings (e.g., particular code cells of interest). This task required participants to transform the notebook into a narrative-oriented workspace, making the workspace accessible to both technical and non-technical audiences, with a focus on visual narrative.

### 7.4.3 Participants and Apparatus

We recruited 20 participants (12 male, 8 female, ages 18 to 35) from a university mailing list, selecting individuals based on their familiarity with data science, machine learning algorithms, and computational notebooks (e.g., Jupyter Notebook). Regarding VR experience, 12 participants had used VR, while the rest had no prior experience. For VR, we used the Meta Quest Pro headset with a resolution of $1800 \times 1920$. It was linked to a PC with an Intel i7-11800H processor and an NVIDIA GeForce RTX 3070 graphics card. To accommodate a larger number of cells, the physical workspace also needed to be expanded. To achieve this, we conducted the study in a $36m^2$ obstacle-free area and utilized Meta Air Link to provide a cable-free experience, allowing participants to move freely throughout the space. For desktop, we used a 27" monitor with a 2560x1440 resolution, allowing participants to view three to four cells simultaneously.

### 7.4.4 Procedure

Our user study followed a full-factorial within-subjects design, counterbalanced using a Latin square. After reviewing the consent form, participants adjusted their chairs and headsets to ensure clear visibility of the text. Training sessions introduced various types of non-linear execution orders and explained the study conditions, with extended VR training provided to lower the learning curve. Training concluded once participants demonstrated task proficiency, typically within 10–15 minutes. Participants then began the study tasks, starting with the first task on the desktop setup before transitioning to the VR environment to complete the remaining tasks. After completing all tasks, participants completed a Likert-scale survey, which included the System Usability Scale (SUS) and NASA Task Load Index (TLX), and provided qualitative feedback on their experience. The entire study lasted approximately 90 minutes and concluded once all questionnaires had been completed.

### 7.4.5 Measures

We collected quantitative data and interaction logs for each study condition from Task 2 until task completion to focus exclusively on the organization process. Specifically, we measured the following: **Time**: the duration from the start of the organization process until the task completion. **Number of Movement**: A recorded sequence of the participant's positions over time. **Travel Distance**: The total distance participants traveled within the environment to complete the task.

In addition to quantitative data, we collected subjective ratings using a seven-point Likert scale to assess **physical demand**, **mental demand**, perceived **difficulty** in organizations, **learn a lot** to use, and overall **preference** for each condition. Finally, we also collected qualitative feedback to gain deeper insights into participants' perceptions and experiences across conditions.

## 7.5 Results

In this section, we report the quantitative results and qualitative feedback for each condition. Statistical significance is denoted using the following: $p < 0.001$ (*), $p < 0.01$ (**), $p < 0.05$

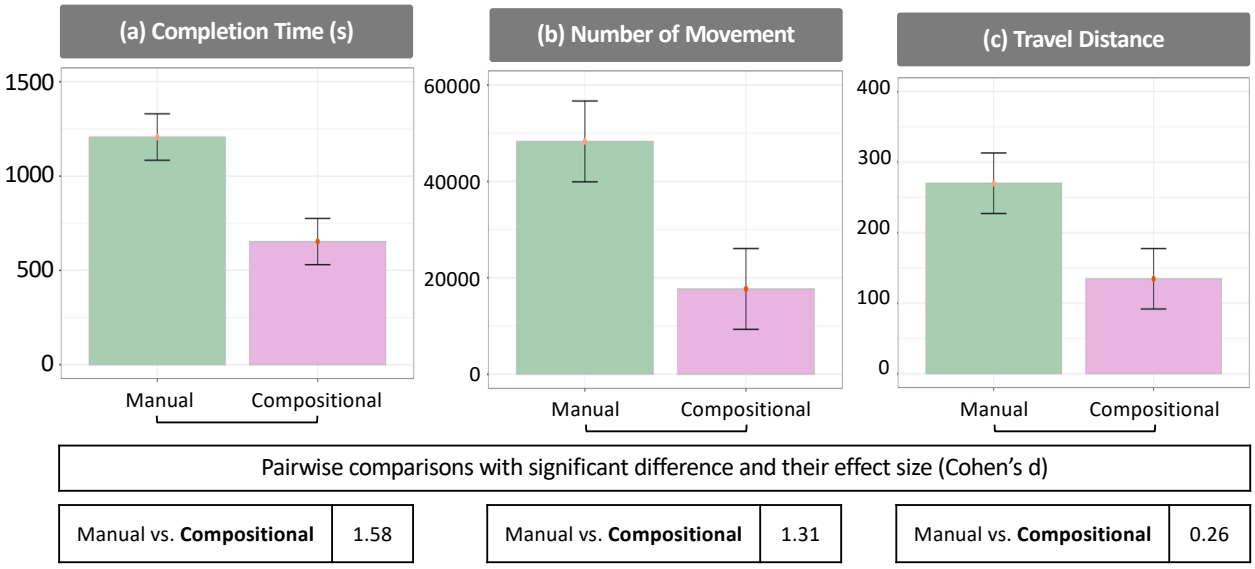



Figure 7.6: Participants' completion time and moved distance across conditions. Solid lines indicate statistical significance with $p < 0.05$, and the tables show effect sizes for pairwise comparisons, with bold text highlighting the outperforming conditions.

(*), and $p < 0.1$ ( $\cdot$ ). Furthermore, we include mean values with 95% confidence intervals (CI) and report Cohen's d to indicate effect sizes. Full statistical results can be found in the supplementary materials.

### 7.5.1 Quantitative Results

The following sections present quantitative results across the conditions, see Fig. 7.6 and Fig. 7.7.

**Time**: We measured completion time in each condition to assess interaction efficiency. Our analysis revealed that completion time was significantly affected by organizational guidance(***). On average, the Manual condition took 1206.90s, while the Compositional took an average of 652.95s, demonstrating that Compositional was 84.97% faster.

**Movement Frequency**: We logged a movement event each time a participant changed position during the study. Our analysis showed that participants in the Compositional moved significantly less than those in the Manual (***). On average, participants in the Manual moved 48,301 times, while those in the Compositional moved 17,694 times—a 172.98% reduction in movement frequency.

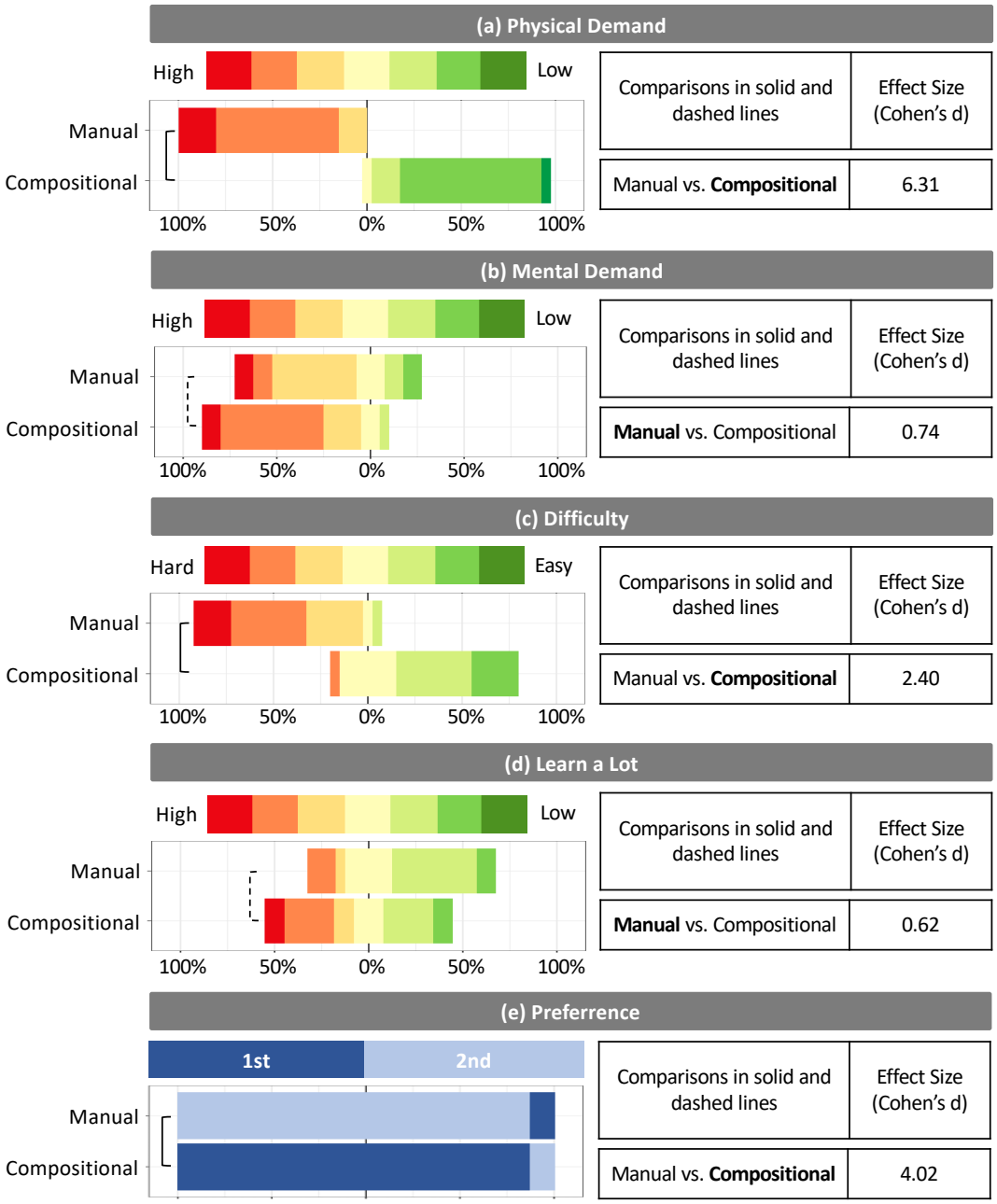



Figure 7.7: Participants' subjective ratings: (a) physical demand, (b) mental demand, (c) difficulty level, (d) learn a lot, and (e) preference. Solid lines indicate statistical significance with $p < 0.01$, and dashed lines indicate statistical significance with $p < 0.05$. Additionally, the tables display effect sizes for pairwise comparisons, with bold text highlighting the conditions that outperform others.

**Travel Distance**: Building on the movement event data, we calculated the total physical distance each participant traveled using the Euclidean distances between consecutive recorded positions. Our findings showed a substantial reduction in total movement distance in the Compositional (***). Participants in the Manual traveled an average of 1,384.72 meters, while those in the Compositional covered only 348.71 meters, indicating a 74.86% reduction in overall movement distance.

**Ratings.** We observed significant effects in both physical demand (***) and perceived difficulty (***), where Compositional outperformed Manual. Specifically, average ratings for physical demand were 5.80 for Manual and 1.95 for Compositional and for perceived difficulty, 4.80 for Manual and 2.35 for Compositional. In addition, the majority of participants preferred the Compositional condition for organizing artifacts in immersive notebooks, with 19 out of 20 participants ranking it as their top choice (***). However, we observed that mental demand (*) and learn a lot (*) shows marginal effects where Manual were outperformed Compositional. Specifically, average ratings for mental demand were 2.45 for Manual and 3.45 for Compositional and for lear a lot to use, 2.70 for Manual and 3.65 for Compositional.

### 7.5.2 Qualitative Feedback.

We performed a qualitative analysis to identify recurring themes in user feedback across each condition. Two authors developed a coding scheme based on feedback from the first five participants, which was then consistently applied to all subsequent data. Finally, we synthesized the key insights across all conditions. Detailed coding results are provided in the supplemental materials.

**Manual.** Participants favored *easier navigation* (11) through embodied interactions and appreciated the *flexibility workspace management* (10), with several noting that the system was *easy to organize* (5). However, nearly all participants reported that manually interacting with cells one by one led to *physical fatigue* (16), with some even *giving up* (7) on organizing artifacts altogether due to the effort required. Some also noted the need to walk closer to view detailed information, as it was *not clearly visible from a distance* (3), which further contributed to the *difficulty in maintaining organization* (9).

**Compositional.** In contrast to the Manual, participants largely commented that the

Compositional condition was easier to organize (19), as it provided a comprehensive set of structures (13) aligned with commonly used coding logic. This led many to feel that they had created well-organized structures (11). Additionally, participants appreciated the intuitive triggering mechanism (7) for invoking the guidance system. However, some participants noted a learning curve during the training session (7). Others expressed concerns about reduced flexibility (5), mentioning that they were unable to adjust spacing within guided structures. Furthermore, as guided structures grew in size, participants found it hard to interact with larger structures (4).

## 7.6 Discussions

**Usability of compositional structuring.** Participants significantly favored the Compositional with an average of 4.7 out of 5 in impressiveness. Additionally, participants reported that the Compositional was easy to use (average 3.8 out of 5), they would like to frequently use the system (4.4 out of 5), various functions were well integrated (4.7 out of 5), and organizing larger number of artifacts were not cumbersome (4.4 out of 5). Moreover, 13 participants felt that the system supported a comprehensive set of execution orders, including both linear and non-linear structures. Furthermore, 19 participants preferred the compositional structuring to organize artifacts in an immersive computational notebook (see Fig. 7.7-(d)) To this end, the Compositional got 80.18 SUS score, indicating that the system is "Acceptable" with "Excellent" adjective rating [128].

**Compositional enabled participants to rapidly build structures with reduced efforts (RQ1).** We observed that the Compositional consistently outperformed the Manual in time and reduced efforts (see Fig. 7.6-(a) and Fig. 7.7-(a)). At the local level, participants in the Manual had to carefully consider both spatial positioning and execution logic while constructing their structures. In contrast, participants could skip such fine-tuning process in Compositional, as it provided well-defined execution logics and spatially aligned layouts. Additionally, a global-level organization was facilitated by the ability to move and position groups of cells at once. It reduced the need for repetitive movements (see Fig. 7.8-(a)) to reposition each cell and associated execution indicators when relocating already constructed structures. One participant (P8) explicitly highlighted the effectiveness of embodied compositional structuring. Participants used the same organizational strategies in both the Manual and Compositional, but completed the task 204% faster in the Compo-

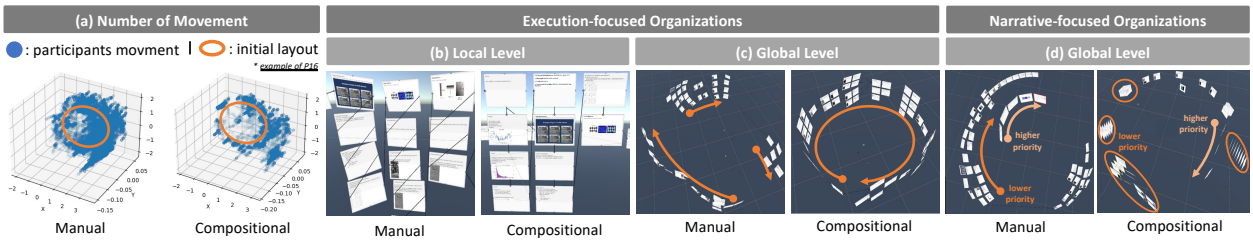



Figure 7.8: Illustrations of comparisons between Manual and Compositional. (a) Participants moved significantly less in the Compositional, as indicated by fewer blue dots. In execution-focused workspaces, (b) Compositional enabled the construction of well-organized structures with clearly positioned execution indicators. (c) Participants in Compositional built more continuous workflows, in contrast to the fragmented workflows observed in the Manual. (d) In narrative-focused workspaces, participants in Compositional actively piled or folded lower-priority cells and hid the execution indicators, while those in Manual largely left their previously built execution-focused structures.

sitional. The subjective ratings further support our findings, where 19 out of 20 participants reported that compositional structuring helped maintain consistent spacing, alignment, and clear execution logic, compared to the Manual. As one participant noted, "I can organize the workflow very easily and fast (P8)".

**Participants still abandoned organizational refinement in Manual, but significantly less in Compositional (RQ2).** Previous studies have identified that participants often abandon organizational refinement when interacting with artifacts one by one manually [142]. Similarly, at the local level, we found that 15 participants in the Manual abandoned careful refinement. Specifically, they let the execution indicators cross over adjacent cells (see Fig. 7.8-(b)), which obscured the code and made the execution logic less interpretable [2]. In contrast, fewer participants (8) in the Compositional abandoned such refinements. At the global level, 10 participants in the Manual abandoned global refinement, compared to only 5 in the Compositional. Participants generally attempted to reorganize their workspaces into a more compact size to reduce the physical effort required in expanded workspaces as the number of cells increased. Ironically, this reorganization process required considerable physical effort, as it involved relocating numerous cells and execution indicators to their main workspace. As a result, the workspaces became fragmented into multiple sections, regardless of the intended analytical structure (see Fig. 7.8-(c)).

Furthermore, we found that 14 participants in Manual also gave up refinements in transitioning the workspace from execution-focused to narrative-focused. Although they expressed

a desire to cluster or stack all non-narrative cells, they ultimately retained the execution-focused structure due to the effort required to reposition them manually (see Fig. 7.8-(d)). In contrast, only 6 participants in the Compositional abandoned such refinements, and the remaining participants actively clustered or folded execution-focused structures, and some even snapped them to hide all execution indicators. In summary, we believe that embodied compositional structuring encourages participants to engage in the refinement process, enabling them to build intended structures even when the number of cells increases and the analytical focus shifts. Our subjective feedback further supports this observation, one participant in the Manual remarked, "It was annoying to organize, so I just gave up on having nice structures (P14)", whereas a participant in the Compositional noted, "I could organize it as I intended, even nicer shape and alignment (P2)".

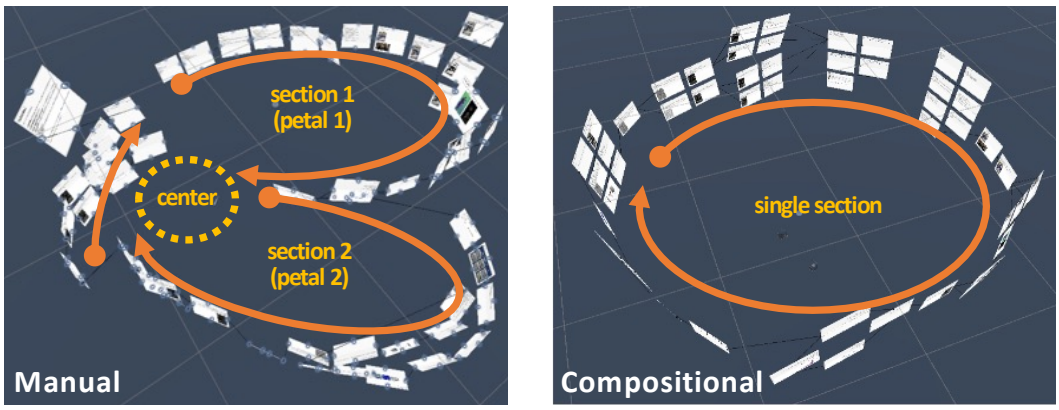
**📖Compositional potentially led participants to similar organizational strategies, in contrast to the more diverse strategies observed in 🤚Manual (RQ3).** We observed that participants tended to have similar organizations in Compositional, particularly at the local level in the execution-focused workspace. Specifically, 11 participants in Compositional transformed all cells in long linear sequences into large-sized single Multi-row or Multi-column Grid structures. However, the majority of participants in the Manual (15) employed more diverse strategies, such as dividing into multiple Multi-row and multi-column Grid structures with a smaller range of cells, enabling them to fit compactly. At the global level, while we did not observe substantial overall differences, we noted one distinctive case among participants who did not abandon organizational refinement in both Manual and Compositional. In Manual, participant P5 arranged their workspace in a flower-like workspace where multiple sections radiating from a center (see Fig. 7.9-(a)). In contrast, in the Compositional, this participant adopted a single-section workspace—consistent with the strategy used by the majority of other participants. Therefore, we believe our findings partially align with prior research suggesting that system-level support can discourage users from conducting additional analysis and may reduce the diversity of approaches to creative problem-solving [158].

**Participants manually build Skip-Layer structure in 📖Compositional (RQ4).** In the Compositional, participants were free to build structures either manually or using the compositions. During narrative-focused tasks, we observed that participants actively adopted the Skip-Layer structure to highlight key findings. However, only 4 participants used the embodied compositional structuring to build Skip-Layer structure during the actual

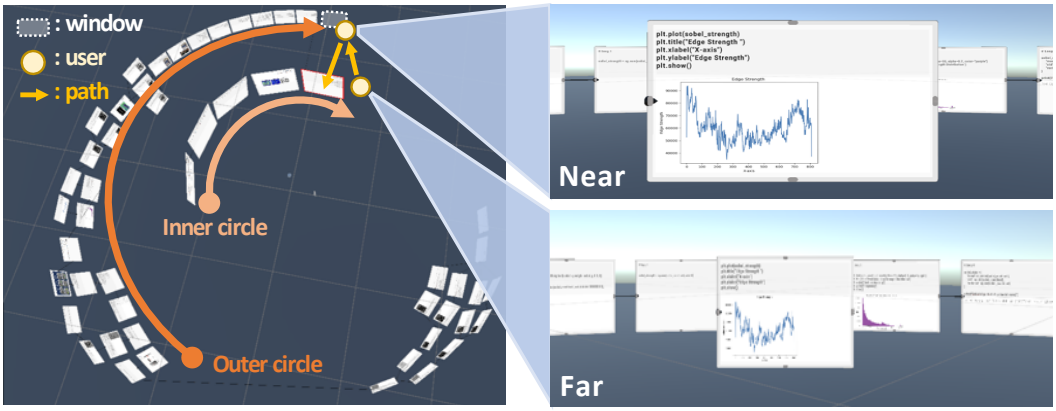
task. Although participants expressed positive impressions of Skip-Layer during the training session, most chose to build Skip-Layers manually. We observed that participants carefully inspected individual cells by walking closer (near) and repositioned high-priority cells to separate areas, organizing them into smaller layers at a distance (far) [155]. We believe a usability issue led to manual interaction on building Skip-Layer: code and outputs were not clearly visible from a distance (see Fig. 7.9-(b)), prompting participants to walk closer for detailed inspection before deciding on placement. This challenge was reflected in participant feedback, such as: "I cannot clearly see the code from a far distance (P1)".

**Gesture-based triggering mechanisms yielded mixed results when applied to a larger set of interactions (RQ4).** Gesture-based interaction provides an intuitive way for performing operations [5, 151]. Similarly, we found that the provided triggering mechanisms were perceived as intuitive by 7 participants, with one participant noting, "Each interaction was intuitive and easy to learn (P15)". Furthermore, one participant (P1) explicitly stated that the Proxy Window helped them perform gestural interactions more clearly, as it provided visual feedback of their actions. However, an equal number of participants (7) reported that the mechanism required considerable effort to learn and remember (also see Fig. 7.7-(d)). Although we conducted an extensive training session and confirmed that participants had memorized the required gestures, all participants requested reminders at least once during the actual tasks as time passed. We believe this led to increased mental demand (see Fig. 7.7-(b)) as participants need to memorize and recall a large set of interactions (13 in total) in Compositional. One participant explicitly mentioned, "It was hard to remember every operation (P13)."

**Limitations&Future Work.** Although embodied compositional structuring accelerated the organization process and reduced the required effort, it also revealed areas for improvement in the triggering mechanism. Specifically, one possible approach to address challenges in building the Skip-Layer structure is to incorporate Focus+Context lenses [151], which are commonly used in the field of visualization to enable access to both overview and detail [159]. Additionally, a Near-Far interaction could be employed [160], where lenses appear only when users are positioned farther away from the content. We believe this approach would not only enhance the intuitiveness of the triggering mechanism but also minimize the physical movement within large immersive spaces. Furthermore, we found that participants had to rely heavily on their memory to interact with a large set of gestures. We believe this challenge arose because gesture-based interaction lacks an overview of available features,




(a) Organizational Strategies of *P5*




(b) Process of Building Skip-Layer

Figure 7.9: Illustrations of unique strategies and behaviors during the organization process. (a) A participant (P5) in the MANUAL created multiple sections from a central point, forming a flower-like shape, with each "petal" representing a sub-task in the analysis. (b) While participants were building Skip-Layer, they moved back and forth, as the content was not clearly visible from a distance.

unlike WIMP interfaces. To address this limitation, we envision integrating gesture interactions and WIMP interfaces. In such a hybrid approach, frequently used or user-preferred operations could be mapped to gestures [161], while others remain accessible via buttons or menus, thereby balancing intuitiveness with scalability.

## 7.7 Conclusion

In this study, we introduced embodied compositional structuring to support the organization process within immersive computational notebooks. Our findings show that it significantly reduced both the time and effort required to organize content, enabling participants to maintain clear execution logic, proper alignment, and spacing. However, compositional structuring also presents trade-offs. While it streamlines the structuring process, it may oversimplify the complex workflow as analysts rely heavily on system-level assistance, potentially limiting opportunities for expressing complex analytical reasoning. In summary, we believe that embodied compositional structuring offers potential for supporting the organizations of immersive computational notebooks in ways that clearly convey analytical intent and improve the usability of immersive workspaces.

# Chapter 8

# Conclusions & Future Works

In this chapter, we take some time to summarise the research projects.

## 8.1 Conclusions

This chapter examines each research question and presents the findings from the user studies conducted to address these questions.

**RQ1: How can VR's Spatial and Embodied nature enhance navigation and comparison in computational notebooks?**

Despite ongoing efforts to enhance navigation and comparison performance in computational notebooks, limitations persist as data science tasks become more complex in traditional desktop environments. To address this, we adapted the computational notebook interface for virtual reality (VR) and evaluated its effectiveness through a controlled user study. Our results showed that VR-based notebooks outperformed desktop notebooks in navigation efficiency, with the introduction of a "branch&merge" feature significantly improving non-linear comparison tasks. Participants reported that the integration of VR with the "branch&merge" functionality was the most engaging and provided the best overall user experience across all test conditions. However, text interaction in VR remains challenging. This limitation could be mitigated by future advancements in hardware and tracking technologies, as well as increased user familiarity with VR environments. Our study highlights the significant potential of computational notebooks in VR, particularly for improving navigation and comparison processes for analysts. It is important to note that our VR adaptation specifically focused on navigation and comparison, and other novel approaches may be explored for adapting or redesigning computational notebooks in VR. Overall, findings offer preliminary evidence supporting the broader use of large display spaces, enhanced spatial awareness, embodied interaction, and physical navigation in VR for immersive analytics applications.

**RQ2: How does VR help Data Transformation?**

Previous explorations of data transformation on desktop settings have highlighted certain limitations. To address these, we introduced prototypes enabling embodied interactions in virtual reality (VR) for data transformation tasks. We conducted a controlled user study to systematically evaluate the effects of computing environments (Desktop vs. VR) and interaction methods (WIMP vs. Gesture). Our findings provide initial evidence of the benefits of using VR for data transformation. Specifically, VR showed potential for enhanced provenance tracking compared to the desktop environment and offered preliminary indications of promoting more strategic thinking. VR also demonstrated a similar time performance to that of the desktop environment. Additionally, participants found VR more engaging overall, with the VR+Gesture combination providing the best user experience. Given the iterative nature of data science, we foresee a strong potential for integrating immersive data transformation and visualization to support a more seamless Immersive Analytics workflow, reducing the overhead of switching between computing environments. We believe there is room for improving gesture-based interactions, such as through long-term training and real-time memory assistance. In summary, our results offer preliminary evidence that the large display space, spatial memory, and embodied navigation in VR are beneficial for high-level data transformation tasks.

**RQ3: How can we incorporate embodied workspace in immersive computational notebooks?**

Existing computational notebooks in traditional desktop environments present challenges in transitioning between different setups for coding, data transformation, and visualization platforms. To address this, we introduce ICoN, a system designed to seamlessly integrate computational notebooks with embodied data science tasks in a unified environment. Our two-user study confirmed that ICoN streamlines the transition between code, data transformation, and visualization, while embodied interactions enable more efficient exploratory capabilities within the data science workflow. However, participants experienced difficulties when spatial relationships within their workflow were unclear, underscoring the need for additional visualization aids and novel interaction approaches to enhance workflow clarity. In summary, ICoN presents an innovative immersive data science workspace by integrating spatial and embodied interactions in immersive environments, offering a novel approach to data analysis and exploration.

**RQ4: What are organizational strategies in the immersive computational notebook?**

Active research on organizational strategies is ongoing, but there is limited exploration when execution order plays a significant role. To address this gap, we aim to enhance our understanding of the spatial structures used in computational notebooks within immersive environments and examine how various execution orders can be visualized compared to desktop setups. Our findings indicate that a half-cylindrical layout is predominantly preferred, with participants favoring a linear execution order with branching, as it facilitates easier comparison of results. Notably, we observed a significant increase in the adoption of non-linear analysis in ICoN compared to desktop environments, highlighting the potential of immersive computational notebooks to encourage more non-linear approaches. Given the frequent need for comparative analysis in real-world scenarios, we believe ICoN offers an environment where analysts can construct workflows more logically and efficiently. However, participants reported challenges in manually moving individual code cells when reorganizing larger amounts of code, suggesting the need for additional support in managing and organizing code cells more effectively in complex workflows.

**RQ5: How can large-scale analysis be effectively organized within immersive computational notebooks?**

Immersive computational notebooks offer greater flexibility in organizing content, allowing users to move beyond linear structures and visually externalize their mental models into more intuitive, non-linear layouts. However, current systems often require analysts to manually interact with each artifact one by one using embodied interaction. This limitation places a heavy burden on users, especially as the number of cells increases, leading to substantial effort in building structured workspaces or abandoning the process. To address these challenges, we introduce embodied compositional structuring to facilitate the organizational process. Our study found that participants were able to complete organizational tasks significantly faster and with far less effort using embodied compositional structuring. However, this approach also introduced trade-offs; participants often became heavily reliant on the system's support, which may reduce their engagement in deeper reasoning and decision-making. Furthermore, to support interaction with a large number of artifacts and to accommodate the diverse use cases of computational notebooks, we provided a total of 13 interaction features. While these were implemented through gestural interactions for fluidity and immersion, we found that participants struggled to recall the required gestures during actual tasks. We believe

this difficulty arose from the lack of an overview or visual proxy, unlike WIMP (Windows, Icons, Menus, Pointer) interfaces, which allow users to view available options at a glance. In summary, while embodied compositional structuring introduces new opportunities for refinement, we believe it holds strong potential for supporting the organization of immersive computational notebooks.

## 8.2 Limitations and Future Works

### 8.2.1 Broader applicapability

Although ICoN aims to facilitate seamless transitions, some improvements, particularly in embodied data visualization, need to be discussed in our system design. While scatter plots are used for a wide range of data science tasks [68, 123, 124], various plot types need to be utilized to comprehensively understand data and discover insights. For instance, line plots can be used to analyze correlations and box plots to examine distributions. Other than visualization types, we recognized that additional interactions are needed for both data transformation and visualization tasks. Enhanced interactivity would facilitate deeper exploration, allowing users to drill down into details and interactively query the data. This could encompass capabilities such as selecting subsets of data and annotating findings directly on the data. In summary, now that the concept of seamless transitions has been validated, future work can expand the range of plot types and include additional interaction to broaden ICoN's applicability in realistic data science tasks.

### 8.2.2 Optimizing interaction for decision-making process

As the number of cells increases, the initial workspace expands significantly, often forming a large ring-like structure. However, one of the limitations identified in our study of embodied compositional structuring is that analysts were unable to clearly see code from a distance (see Chapter. 7). As a result, participants frequently walked long distances within the immersive environment, which introduced substantial physical demands. While alternative navigation techniques such as joystick movement or teleportation can reduce physical effort, they often lead to motion sickness and require users to rapidly reorient themselves to changes in the workspace, disrupting spatial awareness [6]. This highlights a need to address physical

demands while maintaining spatial awareness during analysis.

A promising direction involves leveraging visualization techniques commonly used in analytical workflows. We believe that interaction methods designed for visualization, particularly those that support distant inspection, can be adapted to immersive computational notebooks. Specifically, methods such as focus+context [162] using lenses (e.g., Cartesian lenses [163], fisheye lenses [164]), overview+detail [159], and pan-and-zoom interactions [165] may provide new ways of shaping spatial structures in immersive computational notebooks, enhancing usability at scale. These techniques may help users identify relevant information with fewer interactions and from a greater distance.

While lens-based approaches enable near-far interaction, allowing analysts to interact with low physical demands, they can also be applied in other ways. Prior work has explored using near-far proxies to display summarizations of detailed content when analysts are viewing from afar (e.g., showing only outputs or visualizations), and then revealing detailed information as the analyst moves closer to the cells [160]. Although summarization enables analysts to grasp the embedded information from a distance, not all cells contain visual outputs or narrative elements. Therefore, it is essential to consider summarizing textual content in a concise form, possibly using a few key words or phrases, to ensure the summary remains informative and accessible at a glance. In summary, although both approaches have proven effective for distant inspection in visualization workflows, it remains unclear how these techniques stand out in the context of immersive computational notebooks.

### 8.2.3 Optimizing interaction in selecting objects

In the embodied compositional structuring approach, participants were required to select multiple cells in order to transform a target cell into the desired structure (see Chapter. 7). Participants accomplished this by either clicking on each cell individually or by selecting a range using the first and last cells. We believe this selection method could be further optimized by incorporating a near-far interaction, as the distance from the structure conveys semantic meaning [133, 160]. For instance, when users move closer to the structure, it may indicate a desire for more detailed control, enabling the selection of individual cells. Conversely, when they are positioned farther away, it may suggest interacting with a group of cells at a higher level, enabling group selection with a single click. This approach could be extended by defining dynamic thresholds that determine how many and which types of cells

are grouped together based on spatial relationships, enhancing both efficiency and semantic alignment in the selection process.

### 8.2.4 Learning curve in gestural interaction

We designed a wide range of gesture-based interactions to support the comprehensive use of computational notebooks and to facilitate the organization process in immersive environments (see Chapter. 7). Although participants went through extensive training and demonstrated proficiency in performing all required gestures, we observed that during the actual tasks, they frequently requested reminders about which gestures were needed to execute specific operations. Our findings revealed mixed results to the provided gestural interactions: seven participants reported that the gestures were intuitive and easy to use, while an equal number expressed difficulty in remembering them. This suggests that, despite their initial learnability, gestures became harder to recall in complex workflows. We believe this challenge stems from a fundamental limitation of gesture-based interaction: it lacks a visual overview of available features, in contrast to traditional WIMP (Windows, Icons, Menus, Pointer) interfaces that allow users to browse and select functions more easily.

To address this limitation, we propose a hybrid interaction model that integrates gesture-based interactions with traditional WIMP (Windows, Icons, Menus, Pointer) interfaces. In this scenario, frequently used or user-preferred operations could be mapped to gestures [161], enabling quick, fluid interactions. In contrast, less common or more complex operations would remain accessible through menus or buttons, preserving discoverability and reducing cognitive load. This approach aims to balance intuitiveness and scalability, allowing users to benefit from the expressive nature of gestures without being overwhelmed by memorizing a large number of gestures. Furthermore, we envision that users should have control over this mapping process. That is, users could customize which operations are bound to gestures versus menu-based interactions, depending on their preferences, task frequency, or cognitive comfort. By tailoring the interaction modality to both task context and individual preferences, this hybrid model has the potential to enhance the efficiency, learnability, and overall user experience of immersive computational notebooks.

### 8.2.5 Integrating LLM to support evolving analysis

While ICoN enables users to compare multiple hypotheses by duplicating existing code, the current system primarily supports interactions centered around existing notebook cells. However, in real-world data analysis workflows, analysts often spend a significant portion of their time writing new code rather than interacting with previously written code [2, 70, 71]. To better reflect these real-world scenarios, our system could be extended to support not only existing codes but also code creation. One promising direction is to integrate a large language model (LLM) into the immersive environment. For instance, the system could give existing code snippets to an LLM, which would then analyze the logic, infer semantic relationships between cells, and recommend potential structures from the provided structures in Chapter. 7. Furthermore, as the user writes new code, the model could continuously update its understanding of the evolving workflow and suggest cell grouping strategies that reflect the user's analytical intent. This extension would allow ICoN to move beyond existing code manipulation and into adaptive, real-time collaboration with AI, supporting both exploratory programming and dynamic workflow construction in immersive environments.

### 8.2.6 Transition between Desktop and VR

The ICoN system demonstrates the potential for supporting the full spectrum of data science tasks within immersive environments (see Chapter. 5). However, computationally intensive tasks, such as loading large datasets, are often better handled on desktop setups. This is due to the performance limitations of immersive environments, which must render complex 3D objects and maintain interactive capabilities [166]. In such scenarios, offloading heavy computational tasks to the desktop introduces transition overhead when users move between desktop and immersive environments. Prior work has explored the impacts of transition experience between desktop and VR environments. For instance, RELIVE demonstrated that seamless transitions between desktop and VR could enhance analytical workflows [135]. However, their focus was primarily on transferring visualizations between 2D and 3D with basic manipulations; the underlying code logic and notebook structure were not addressed.

When working with code, especially in computational notebooks, additional considerations arise. Unlike visualizations, code is typically presented in a linear, top-to-bottom format on desktop [2], and translating the linearity into immersive environments poses unique chal-

lenges. Simply replicating the linear layout in VR underutilizes the spatial affordances of immersive systems, where alternative layouts—such as grids, branches, or loops—may offer clearer representations of the analytical process. The key challenge, then, is determining which layout strategies best preserve the structure and intent of the code while leveraging the spatial awareness of immersive environments.

In summary, designing effective transitions between desktop and immersive environments remains a critical research direction—especially in the context of computational notebooks—where balancing computational performance, spatial clarity, and cognitive continuity is essential to supporting scalable and fluid data science workflows.

### 8.2.7 Scalability in embodied data transformation

Furthermore, we also tested relatively small data in our study of embodied data transformation (see Sec. 4.3.4), as we want to control the study duration. Meanwhile, we had an interesting comment from one participant: They did not actively check the rows of data tables but focused more on the columns. This comment aligns well with the design of the GestureDB system [27, 29], where they present the columns all the time and only present rows on demand or for confirmation purposes. Larger data should be tested in future studies, especially with more columns. Meanwhile, displaying all columns for large data sets (e.g., with 20 columns) is challenging. As such, we intentionally have columns that cannot fit into the table view in our tested data. The width of each column was determined by its longest data entry, causing the total width of all columns to exceed the table's width. Hence, even with a limited number of columns, columns were not visible immediately, and scrolling was necessary to finish the task. From this perspective, we anticipate that, with increasing data size, participants need to scroll more, making the task more challenging for all conditions.

Precision is often required when scrolling, so increasing the data size may affect VR more than the Desktop. On the other hand, it is possible to leverage the large display space in VR to alleviate this issue: we can use a large space to ensure all columns are visible without the need to scroll in VR. The user can then physically move in the space to navigate the large data tables. Physical navigation has been more effective than virtual navigation, like panning or scrolling [110]. However, additional interaction supports are likely needed (e.g., shrinking the table size when grabbed) and should be tested in future work.

### 8.2.8 Collaborations

Another promising direction for future work involves enhancing collaboration within immersive computational notebooks. While traditional notebooks support sharing or commenting via platforms like JupyterHub [167] or Google Colab [75], immersive environments offer the potential for real-time, co-located or remote collaborative analysis using spatial metaphors. Analysts could organize content jointly in a shared 3D space, negotiate the structure of narratives, or annotate computational artifacts in context. However, collaboration in immersive environments also introduces new challenges, such as managing shared execution order, coordinating viewpoint and focus, and resolving conflicting changes in notebook state. Future work should explore how to design interaction models that support synchronous and asynchronous collaboration, while preserving clarity, authorship, and intent in the evolving structure of a shared immersive notebook.

# Bibliography


[1] T. Kluyver, B. Ragan-Kelley, F. Pérez, B. Granger, M. Bussonnier, J. Frederic, K. Kelley, J. Hamrick, J. Grout, S. Corlay, P. Ivanov, D. Avila, S. Abdalla, and C. Willing, "Jupyter notebooks – a publishing format for reproducible computational workflows," in *Positioning and Power in Academic Publishing: Players, Agents and Agendas* (F. Loizides and B. Schmidt, eds.), pp. 87 – 90, IOS Press, 2016.

[2] S. Chattopadhyay, I. Prasad, A. Z. Henley, A. Sarma, and T. Barik, "What's wrong with computational notebooks? pain points, needs, and design opportunities," in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2020.

[3] B. Ens, B. Bach, M. Cordeil, U. Engelke, M. Serrano, W. Willett, A. Prouzeau, C. Anthes, W. Büschel, C. Dunne, *et al.*, "Grand challenges in immersive analytics," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pp. 1–17, 2021.

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

[5] M. Cordeil, A. Cunningham, B. Bach, C. Hurter, B. H. Thomas, K. Marriott, and T. Dwyer, "Iatk: An immersive analytics toolkit," in *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 200–209, IEEE, 2019.

[6] Y. Yang, M. Cordeil, J. Beyer, T. Dwyer, K. Marriott, and H. Pfister, "Embodied navigation in immersive abstract data visualization: Is overview+ detail or zooming better for 3d scatterplots?," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 2, pp. 1214–1224, 2020.

[7] F. Yang, J. Qian, J. Novotny, D. Badre, C. D. Jackson, and D. H. Laidlaw, "A Virtual Reality Memory Palace Variant Aids Knowledge Retrieval from Scholarly Articles," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, pp. 4359–4373, Dec. 2021.

[8] M. Cordeil, A. Cunningham, T. Dwyer, B. H. Thomas, and K. Marriott, "Imaxes: Immersive axes as embodied affordances for interactive multivariate data visualisation," in *Proceedings of the 30th annual ACM symposium on user interface software and technology*, pp. 71–83, 2017.

[9] H. Wickham and G. Grolemund, *R for data science: import, tidy, transform, visualize, and model data.* " O'Reilly Media, Inc.", 2016.

[10] A. Rule, A. Tabard, and J. D. Hollan, "Exploration and explanation in computational notebooks," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2018.

[11] R. D. Peng, "Reproducible research in computational science," *Science*, vol. 334, no. 6060, pp. 1226–1227, 2011.

[12] JupyterNotebook, "Computational notebook tool." https://jupyter.org/, 2023. Accessed: 2023-1-15.

[13] JupyterNotebook, "Jupyter survey." https://github.com/jupyter/surveys/blob/master/surveys/2020-12-jupyter-survey/README.md, 2020. Accessed: 2023-8-31.

[14] Observable, "Computational notebook tool." https://observablehq.com/, 2023. Accessed: 2023-1-15.

[15] A. Camel, "Apache camel data flow system." https://zeppelin.apache.org/, 2024. Accessed: 2024-2-28.

[16] S. In, E. Krokos, K. Whitley, C. North, and Y. Yang, "Evaluating navigation and comparison performance of computational notebooks on desktop and in virtual reality," in *Proceedings of the CHI Conference on Human Factors in Computing Systems*, pp. 1–15, 2024.

[17] Y. Zhao, J. Jiang, Y. Chen, R. Liu, Y. Yang, X. Xue, and S. Chen, "Metaverse: Perspectives from graphics, interactions and visualization," *Visual Informatics*, vol. 6, no. 1, pp. 56–67, 2022.

[18] H. B. Surale, A. Gupta, M. Hancock, and D. Vogel, "Tabletinvr: Exploring the design space for using a multi-touch tablet in virtual reality," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–13, 2019.

[19] T. Drey, J. Gugenheimer, J. Karlbauer, M. Milo, and E. Rukzio, "Vrsketchin: Exploring the design space of pen and tablet interaction for 3d sketching in virtual reality," in *Proceedings of the 2020 CHI conference on human factors in computing systems*, pp. 1–14, 2020.

[20] V. Biener, D. Schneider, T. Gesslein, A. Otte, B. Kuth, P. O. Kristensson, E. Ofek, M. Pahud, and J. Grubert, "Breaking the screen: Interaction across touchscreen boundaries in virtual reality for mobile knowledge workers," *IEEE transactions on visualization and computer graphics*, vol. 26, no. 12, pp. 3490–3502, 2020.

[21] S. Houben, N. Marquardt, J. Vermeulen, C. Klokmose, J. Schöning, H. Reiterer, and C. Holz, "Opportunities and challenges for cross-device interactions in the wild," *interactions*, vol. 24, no. 5, pp. 58–63, 2017.

[22] M. B. Kery, M. Radensky, M. Arya, B. E. John, and B. A. Myers, "The story in the notebook: Exploratory data science using a literate programming tool," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1–11, 2018.

[23] R. Sicat, J. Li, J. Choi, M. Cordeil, W.-K. Jeong, B. Bach, and H. Pfister, "Dxr: A toolkit for building immersive data visualizations," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 715–725, 2018.

[24] T. P. Builder, "Tableauprep." https://www.tableau.com/products/prep, 2022. Accessed: 2022-08-28.

[25] Trifacta, "Trifacta." https://www.trifacta.com/, 2022. Accessed: 2022-08-28.

[26] Alteryx, "Alteryx." https://www.alteryx.com/, 2022. Accessed: 2022-08-28.

[27] A. Nandi, L. Jiang, and M. Mandel, "Gestural query specification," *Proceedings of the VLDB Endowment*, vol. 7, no. 4, pp. 289–300, 2013.

[28] A. Nandi and M. Mandel, "The interactive join: recognizing gestures for database queries," in *CHI'13 Extended Abstracts on Human Factors in Computing Systems*, pp. 1203–1208, 2013.

[29] L. Jiang, M. Mandel, and A. Nandi, "Gesturequery: A multitouch database query interface," *Proceedings of the VLDB Endowment*, vol. 6, no. 12, pp. 1342–1345, 2013.

[30] S. In, T. Lin, C. North, H. Pfister, and Y. Yang, "This is the table i want! interactive data transformation on desktop and in virtual reality," *IEEE Transactions on Visualization and Computer Graphics*, 2023.

[31] P. Knierim, T. Kosch, J. Groschopp, and A. Schmidt, "Opportunities and challenges of text input in portable virtual reality," in *Extended abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–8, 2020.

[32] R. Ball, C. North, and D. A. Bowman, "Move to improve: promoting physical navigation to increase user performance with large displays," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '07*, (San Jose, California, USA), pp. 191–200, ACM Press, 2007.

[33] J. Liu, A. Prouzeau, B. Ens, and T. Dwyer, "Design and evaluation of interactive small multiples data visualisation in immersive spaces," in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 588–597, IEEE, 2020.

[34] K. A. Satriadi, B. Ens, M. Cordeil, T. Czauderna, and B. Jenny, "Maps around me: 3d multiview layouts in immersive spaces," *Proceedings of the ACM on Human-Computer Interaction*, vol. 4, no. ISS, pp. 1–20, 2020.

[35] J. Liu, B. Ens, A. Prouzeau, J. Smiley, I. K. Nixon, S. Goodwin, and T. Dwyer, "Datadancing: An exploration of the design space for visualisation view management for 3d surfaces and spaces," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pp. 1–17, 2023.

[36] S. In, E. Krokos, K. Whitley, C. North, and Y. Yang, "Icon: Immersive computational notebook with embodied data transformation and visualization," in *2024 The ACM Symposium on User Interface Software and Technology(UIST)*, 2024.

[37] C. Collins, N. Andrienko, T. Schreck, J. Yang, J. Choo, U. Engelke, A. Jena, and T. Dwyer, "Guidance in the human–machine analytics process," *Visual Informatics*, vol. 2, no. 3, pp. 166–180, 2018.

[38] E. Yılmaz, A. Elen, E. Kuran, and E. Kaya, "A comparison of open-source learning management systems used for distance education in higher education institutions," *Journal of Scientific and Vocational Studies*, 2024.

[39] B. E. Plimmer and M. Apperley, "Using shared displays to support group design," tech. rep., University of Auckland, 2004.

[40] S. Shen, Z. Lin, W. Liu, C. Xin, W. Dai, and S. Chen, "Dashchat: Interactive authoring of industrial dashboard design prototypes through conversation with llm-powered agents," 2025.

[41] A. M. George, "Remote collaboration in the design studio," Master's thesis, Texas A&M University, 2005.

[42] Figma, "Figma: The collaborative interface design tool," 2024. Accessed: 2025-04-30.

[43] Miro, "Miro." https://miro.com/, 2020. Accessed: 2022-08-28.

[44] N. Weinman, S. M. Drucker, T. Barik, and R. DeLine, "Fork it: Supporting stateful alternatives in computational notebooks," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2021.

[45] D. Kang, T. Ho, N. Marquardt, B. Mutlu, and A. Bianchi, "Toonnote: Improving communication in computational notebooks using interactive data comics," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pp. 1–14, 2021.

[46] M. B. Kery, A. Horvath, and B. A. Myers, "Variolite: Supporting exploratory programming by data scientists.," in *CHI*, vol. 10, pp. 3025453–3025626, 2017.

[47] R. DeLine, A. Bragdon, K. Rowan, J. Jacobsen, and S. P. Reiss, "Debugger canvas: industrial experience with the code bubbles paradigm," in *2012 34th International Conference on Software Engineering (ICSE)*, pp. 1064–1073, IEEE, 2012.

[48] D. Raghunandan, A. Roy, S. Shi, N. Elmqvist, and L. Battle, "Code code evolution: Understanding how people change data science notebooks over time," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2023.

[49] L. Lisle, K. Davidson, E. J. Gitre, C. North, and D. A. Bowman, "Sensemaking Strategies with Immersive Space to Think," in *2021 IEEE Virtual Reality and 3D User Interfaces (VR)*, (Lisboa, Portugal), pp. 529–537, IEEE, Mar. 2021.

[50] K. Davidson, L. Lisle, K. Whitley, D. A. Bowman, and C. North, "Exploring the evolution of sensemaking strategies in immersive space to think," *IEEE Transactions on Visualization and Computer Graphics*, 2022.

[51] G. Reiske, S. In, and Y. Yang, "Multi-focus querying of the human genome information on desktop and in virtual reality: an evaluation," in *2023 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, pp. 1123–1131, IEEE, 2023.

[52] W. Tong, M. Xia, K. K. Wong, D. A. Bowman, T.-C. Pong, H. Qu, and Y. Yang, "Towards an understanding of distributed asymmetric collaborative visualization on problem-solving," in *2023 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*, pp. 387–397, IEEE, 2023.

[53] H. H. Huang, H. Pfister, and Y. Yang, "Is embodied interaction beneficial? a study on navigating network visualizations," *Information Visualization*, vol. 22, no. 3, pp. 169–185, 2023.

[54] D. A. Bowman, E. Kruijff, J. J. LaViola, and I. Poupyrev, *3D User Interfaces: Theory and Practice*. USA: Addison Wesley Longman Publishing Co., Inc., 2004.

[55] N. C. Nilsson, S. Serafin, F. Steinicke, and R. Nordahl, "Natural Walking in Virtual Reality: A Review," *Computers in Entertainment*, vol. 16, pp. 1–22, Apr. 2018.

[56] M. Plumlee and C. Ware, "Zooming, multiple windows, and visual working memory," in *Proceedings of the Working Conference on Advanced Visual Interfaces - AVI '02*, (Trento, Italy), p. 59, ACM Press, 2002.

[57] M. D. Plumlee and C. Ware, "Zooming versus multiple window interfaces: Cognitive costs of visual comparisons," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 13, pp. 179–209, June 2006.

[58] J. Liu, N. Boukhelifa, and J. R. Eagan, "Understanding the role of alternatives in data analysis practices," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 66–76, 2019.

[59] C. Andrews, A. Endert, and C. North, "Space to think: large high-resolution displays for sensemaking," in *Proceedings of the SIGCHIConference on Human Factors in Computing Systems*, pp. 55–64, 2010.

[60] J. Liu, A. Prouzeau, B. Ens, and T. Dwyer, "Effects of display layout on spatial memory for immersive environments," *Proceedings of the ACM on Human-Computer Interaction*, vol. 6, no. ISS, pp. 468–488, 2022.

[61] J. M. Rzeszotarski and A. Kittur, "Kinetica: Naturalistic multi-touch data visualization," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 897–906, 2014.

[62] Meta, "Meta physical trackable keyboard." https://www.meta.com/help/quest/articles/headsets-and-accessories/meta-quest-accessories/tracked-keyboards-meta-quest/, 2023. Accessed: 2023-1-15.

[63] J. S. Pierce, B. C. Stearns, and R. Pausch, "Voodoo dolls: seamless interaction at multiple scales in virtual environments," in *Proceedings of the 1999 symposium on Interactive 3D graphics*, pp. 141–145, 1999.

[64] S. Alspaugh, N. Zokaei, A. Liu, C. Jin, and M. A. Hearst, "Futzing and moseying: Interviews with professional data analysts on exploration practices," *IEEE transactions on visualization and computer graphics*, vol. 25, no. 1, pp. 22–31, 2018.

[65] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[66] E. Krokos, C. Plaisant, and A. Varshney, "Virtual memory palaces: immersion aids recall," *Virtual reality*, vol. 23, pp. 1–15, 2019.

[67] J. Harden, E. Christman, N. Kirshenbaum, J. Wenskovitch, J. Leigh, and C. North, "Exploring organization of computational notebook cells in 2d space," in *2022 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*, pp. 1–6, IEEE, 2022.

[68] B. Bach, R. Sicat, J. Beyer, M. Cordeil, and H. Pfister, "The Hologram in My Hand: How Effective is Interactive Exploration of 3D Visualizations in Immersive Tangible Augmented Reality?," *IEEE Transactions on Visualization and Computer Graphics*, vol. 24, pp. 457–467, Jan. 2018.

[69] J. A. Wagner Filho, M. F. Rey, C. M. Freitas, and L. Nedel, "Immersive visualization of abstract information: An evaluation on dimensionally-reduced data scatterplots," in *2018 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 483–490, IEEE, 2018.

[70] S. Kandel, A. Paepcke, J. Hellerstein, and J. Heer, "Wrangler: Interactive visual specification of data transformation scripts," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (Vancouver BC Canada), pp. 3363–3372, ACM, May 2011.

[71] P. J. Guo, S. Kandel, J. M. Hellerstein, and J. Heer, "Proactive wrangling: Mixed-initiative end-user programming of data transformation scripts," in *Proceedings of the 24th annual ACM symposium on User interface software and technology*, pp. 65–74, 2011.

[72] S. Kandel, J. Heer, C. Plaisant, J. Kennedy, F. Van Ham, N. H. Riche, C. Weaver, B. Lee, D. Brodbeck, and P. Buono, "Research directions in data wrangling: Visualizations and transformations for usable and credible data," *Information Visualization*, vol. 10, no. 4, pp. 271–288, 2011.

[73] T. Desktop, "Tableau desktop." https://www.tableau.com/products/desktop, 2022. Accessed: 2022-08-28.

[74] Amazon, "Aws auto ml solutions." https://aws.amazon.com/machine-learning/automl, 2022. Accessed: 2022-08-28.

[75] Google, "Automl." https://cloud.google.com/automl/, 2022. Accessed: 2022-08-28.

[76] D. Wang, J. Andres, J. D. Weisz, E. Oduor, and C. Dugan, "AutoDS: Towards Human-Centered Automation of Data Science," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, (Yokohama Japan), pp. 1–12, ACM, May 2021.

[77] B. Saket, A. Srinivasan, E. D. Ragan, and A. Endert, "Evaluating interactive graphical encodings for data visualization," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 3, pp. 1316–1330, 2017.

[78] B. Saket, S. Huron, C. Perin, and A. Endert, "Investigating direct manipulation of graphical encodings as a method for user interaction," *IEEE transactions on visualization and computer graphics*, vol. 26, no. 1, pp. 482–491, 2019.

[79] A. Sarvghad, B. Saket, A. Endert, and N. Weibel, "Embedded Merge & Split: Visual Adjustment of Data Grouping," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, pp. 800–809, Jan. 2019.

[80] S. M. Drucker, D. Fisher, R. Sadana, J. Herron, and m. schraefel, "TouchViz: A case study comparing two interfaces for data analytics on tablets," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (Paris France), pp. 2301–2310, ACM, Apr. 2013.

[81] O.-H. Kwon, C. Muelder, K. Lee, and K.-L. Ma, "A study of layout, rendering, and interaction methods for immersive graph visualization," *IEEE transactions on visualization and computer graphics*, vol. 22, no. 7, pp. 1802–1815, 2016.

[82] L. Lisle, X. Chen, J. Edward Gitre, C. North, and D. A. Bowman, "Evaluating the Benefits of the Immersive Space to Think," in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, (Atlanta, GA, USA), pp. 331–337, IEEE, Mar. 2020.

[83] Y. Yang, T. Dwyer, K. Marriott, B. Jenny, and S. Goodwin, "Tilt map: Interactive transitions between choropleth map, prism map and bar chart in immersive environments," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 12, pp. 4507–4519, 2020.

[84] B. Bach, R. Sicat, J. Beyer, M. Cordeil, and H. Pfister, "The hologram in my hand: How effective is interactive exploration of 3d visualizations in immersive tangible augmented reality?," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 1, pp. 457–467, 2017.

[85] D. Mendes, F. Relvas, A. Ferreira, and J. Jorge, "The benefits of dof separation in mid-air 3d object manipulation," in *Proceedings of the 22nd ACM conference on virtual reality software and technology*, pp. 261–268, 2016.

[86] D. Hayatpur, H. Xia, and D. Wigdor, "Datahop: Spatial data exploration in virtual reality," in *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology*, pp. 818–828, 2020.

[87] S. Kasica, C. Berret, and T. Munzner, "Table Scraps: An Actionable Framework for Multi-Table Data Wrangling From An Artifact Study of Computational Journalism," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, pp. 957–966, Feb. 2021.

[88] Google, "Jamboard." https://jamboard.google.com/, 2020. Accessed: 2022-08-28.

[89] Microsoft, "Whiteboard." https://whiteboard.office.com, 2020. Accessed: 2022-08-28.

[90] T. Marrinan, J. Aurisano, A. Nishimoto, K. Bharadwaj, V. Mateevitsi, L. Renambot, L. Long, A. Johnson, and J. Leigh, "Sage2: A new approach for data intensive collaboration using scalable resolution shared displays," in *10th IEEE International Conference on Collaborative Computing: Networking, Applications and Worksharing*, pp. 177–186, IEEE, 2014.

[91] N. Kodagoda, S. Attfield, B. L. W. Wong, C. Rooney, and S. Choudhury, "Using Interactive Visual Reasoning to Support Sense-Making: Implications for Design," *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, pp. 2217–2226, Dec. 2013.

[92] N. Elmqvist, J. Stasko, and P. Tsigas, "DataMeadow: A Visual Canvas for Analysis of Large-Scale Multivariate Data," in *2007 IEEE Symposium on Visual Analytics Science and Technology*, (Sacramento, CA, USA), pp. 187–194, IEEE, Oct. 2007.

[93] W. Javed and N. Elmqvist, "ExPlates: Spatializing Interactive Analysis to Scaffold Visual Exploration," *Computer Graphics Forum*, vol. 32, pp. 441–450, June 2013.

[94] W. S. Lages and D. A. Bowman, "Walking with adaptive augmented reality workspaces: design and usage patterns," in *Proceedings of the 24th International Conference on Intelligent User Interfaces*, pp. 356–366, 2019.

[95] V. Raman and J. M. Hellerstein, "Potter's wheel: An interactive data cleaning system," in *VLDB*, vol. 1, pp. 381–390, 2001.

[96] J. Chen, H. Cai, A. P. Auchus, and D. H. Laidlaw, "Effects of stereo and screen size on the legibility of three-dimensional streamtube visualization," *IEEE transactions on Visualization and Computer Graphics*, vol. 18, no. 12, pp. 2130–2139, 2012.

[97] L. Arms, D. Cook, and C. Cruz-Neira, "The benefits of statistical visualization in an immersive environment," in *Proceedings IEEE Virtual Reality (Cat. No. 99CB36316)*, pp. 88–95, IEEE, 1999.

[98] R. Ball and C. North, "Analysis of user behavior on high-resolution tiled displays," in *IFIP Conference on Human-Computer Interaction*, pp. 350–363, Springer, 2005.

[99] H. C. Purchase, E. Hoggan, and C. Görg, "How important is the "mental map"?–an empirical investigation of a dynamic graph layout algorithm," in *International Symposium on Graph Drawing*, pp. 184–195, Springer, 2006.

[100] K. Reda, A. E. Johnson, M. E. Papka, and J. Leigh, "Effects of display size and resolution on user behavior and insight acquisition in visual exploration," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 2759–2768, 2015.

[101] F. Yang, J. Qian, J. Novotny, D. Badre, C. D. Jackson, and D. H. Laidlaw, "A virtual reality memory palace variant aids knowledge retrieval from scholarly articles," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 12, pp. 4359–4373, 2020.

[102] J. Zagermann, U. Pfeil, D. Fink, P. von Bauer, and H. Reiterer, "Memory in motion: The influence of gesture-and touch-based input modalities on spatial memory," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 1899–1910, 2017.

[103] D. Bates, M. Mächler, B. Bolker, and S. Walker, "Fitting Linear Mixed-Effects Models Using **lme4**," *Journal of Statistical Software*, vol. 67, no. 1, 2015.

[104] A. Field, J. Miles, and Z. Field, *Discovering statistics using R*. Sage publications, 2012.

[105] R. V. Lenth, "Least-Squares Means: The *R* Package **lsmeans**," *Journal of Statistical Software*, vol. 69, no. 1, 2016.

[106] A. Fonnet and Y. Prie, "Survey of immersive analytics," *IEEE transactions on visualization and computer graphics*, vol. 27, no. 3, pp. 2101–2122, 2019.

[107] J. Wang, D. Crawl, S. Purawat, M. Nguyen, and I. Altintas, "Big data provenance: Challenges, state of the art and opportunities," in *2015 IEEE international conference on big data (Big Data)*, pp. 2509–2516, IEEE, 2015.

[108] Y. L. Simmhan, B. Plale, and D. Gannon, "A survey of data provenance in e-science," *ACM Sigmod Record*, vol. 34, no. 3, pp. 31–36, 2005.

[109] R. Ball and C. North, "Effects of tiled high-resolution display on basic visualization and navigation tasks," in *CHI'05 extended abstracts on Human factors in computing systems*, pp. 1196–1199, 2005.

[110] R. Ball, C. North, and D. A. Bowman, "Move to improve: promoting physical navigation to increase user performance with large displays," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 191–200, 2007.

[111] A. Batch, A. Cunningham, M. Cordeil, N. Elmqvist, T. Dwyer, B. H. Thomas, and K. Marriott, "There is no spoon: Evaluating performance, space use, and presence with expert domain users in immersive analytics," *IEEE transactions on visualization and computer graphics*, vol. 26, no. 1, pp. 536–546, 2019.

[112] W. Luo, A. Lehmann, H. Widengren, and R. Dachselt, "Where should we put it? layout and placement strategies of documents in augmented reality for collaborative sensemaking," in *CHI Conference on Human Factors in Computing Systems*, pp. 1–16, 2022.

[113] Q. Zhu, T. Lu, S. Guo, X. Ma, and Y. Yang, "Compositingvis: Exploring interactions for creating composite visualizations in immersive environments," *arXiv preprint arXiv:2408.02240*, 2024.

[114] A. Tabard, W. E. Mackay, and E. Eastmond, "From individual to collaborative: the evolution of prism, a hybrid laboratory notebook," in *Proceedings of the 2008 ACM conference on Computer supported cooperative work*, pp. 569–578, 2008.

[115] M. Czikszentmihalyi, *Flow: The psychology of optimal experience*. New York: Harper & Row, 1990.

[116] N. Elmqvist, A. V. Moere, H.-C. Jetter, D. Cernea, H. Reiterer, and T. Jankun-Kelly, "Fluid interaction for information visualization," *Information Visualization*, vol. 10, no. 4, pp. 327–340, 2011.

[117] N. C. Nilsson, S. Serafin, F. Steinicke, and R. Nordahl, "Natural walking in virtual reality: A review," *Computers in Entertainment (CIE)*, vol. 16, no. 2, pp. 1–22, 2018.

[118] T. Horak, P. Berger, H. Schumann, R. Dachselt, and C. Tominski, "Responsive matrix cells: A focus+ context approach for exploring and editing multivariate graphs," *IEEE Transactions on Visualization and Computer Graphics*, vol. 27, no. 2, pp. 1644–1654, 2020.

[119] D. A. Norman and S. W. Draper, eds., *User Centered System Design: New Perspectives on Human-Computer Interaction*. Hillsdale, NJ: L. Erlbaum Associates, 1986.

[120] MatplotLib, "Visualizations tools in computational notebook." https://matplotlib.org/, 2024. Accessed: 2024-2-29.

[121] Seaborn, "Visualizations tools in computational notebook." https://seaborn.pydata.org/, 2024. Accessed: 2024-2-29.

[122] Pandas, "Visualizations tools in computational notebook." https://pandas.pydata.org/, 2024. Accessed: 2024-2-29.

[123] M. Cordeil, A. Cunningham, T. Dwyer, B. H. Thomas, and K. Marriott, "ImAxes: Immersive Axes as Embodied Affordances for Interactive Multivariate Data Visualisation," the 30th Annual ACM Symposium on User Interface Software and Technology, pp. 71–83, Oct. 2017.

[124] A. Fonnet, T. Vigier, Y. Prie, G. Cliquet, and F. Picarougne, "Axes and coordinate systems representations for immersive analytics of multi-dimensional data," in *2018 International Symposium on Big Data Visual and Immersive Analytics (BDVA)*, pp. 1–10, IEEE, 2018.

[125] I. Drosos, T. Barik, P. J. Guo, R. DeLine, and S. Gulwani, "Wrex: A unified programming-by-example interaction for synthesizing readable code for data scientists," in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2020.

[126] M. B. Kery, D. Ren, F. Hohman, D. Moritz, K. Wongsuphasawat, and K. Patel, "mage: Fluid moves between code and graphical work in computational notebooks," in *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology*, pp. 140–151, 2020.

[127] Unity, "Python package unity." https://docs.unity3d.com/Packages/com.unity.scripting.python@7.0/manual/index.html, 2023. Accessed: 2023-1-15.

[128] A. Bangor, P. T. Kortum, and J. T. Miller, "An empirical evaluation of the system usability scale," *Intl. Journal of Human–Computer Interaction*, vol. 24, no. 6, pp. 574–594, 2008.

[129] C. M. Ashworth, "Structured systems analysis and design method (ssadm)," *Information and Software Technology*, vol. 30, no. 3, pp. 153–163, 1988.

[130] B. Yu and C. T. Silva, "Visflow-web-based visualization framework for tabular data with a subset flow model," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 251–260, 2016.

[131] M. Bertier, D. Frey, R. Guerraoui, A.-M. Kermarrec, and V. Leroy, "The gossple anonymous social network," in *ACM/IFIP/USENIX International Conference on Distributed Systems Platforms and Open Distributed Processing*, pp. 191–211, Springer, 2010.

[132] J. J. Levandoski, M. Sarwat, A. Eldawy, and M. F. Mokbel, "Lars: A location-aware recommender system," in *2012 IEEE 28th international conference on data engineering*, pp. 450–461, IEEE, 2012.

[133] D. Enriquez, W. Tong, C. North, H. Qu, and Y. Yang, "Evaluating layout dimensionalities in pc+ vr asymmetric collaborative decision making," *arXiv preprint arXiv:2408.05105*, 2024.

[134] J. Müller, R. Rädle, and H. Reiterer, "Remote collaboration with mixed reality displays: How shared virtual landmarks facilitate spatial referencing," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 6481–6486, 2017.

[135] S. Hubenschmid, J. Wieland, D. I. Fink, A. Batch, J. Zagermann, N. Elmqvist, and H. Reiterer, "Relive: Bridging in-situ and ex-situ visual analytics for analyzing mixed reality user studies," in *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, pp. 1–20, 2022.

[136] M. I. Ahmad, I. Keller, D. A. Robb, and K. S. Lohan, "A framework to estimate cognitive load using physiological data," *Personal and Ubiquitous Computing*, pp. 1–15, 2023.

[137] G. Mancusi, A. Panariello, A. Porrello, M. Fabbri, S. Calderara, and R. Cucchiara, "Trackflow: Multi-object tracking with normalizing flows," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 9531–9543, 2023.

[138] N. Elmqvist, N. Henry, Y. Riche, and J.-D. Fekete, "Melange: space folding for multi-focus interaction," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1333–1342, 2008.

[139] A. Head, F. Hohman, T. Barik, S. M. Drucker, and R. DeLine, "Managing messes in computational notebooks," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pp. 1–12, 2019.

[140] R. A. DeLine, "Glinda: Supporting Data Science with Live Programming, GUIs and a Domain-specific Language," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, (Yokohama Japan), pp. 1–11, ACM, May 2021.

[141] B. Hartmann, L. Yu, A. Allison, Y. Yang, and S. R. Klemmer, "Design as exploration: creating interface alternatives through parallel authoring and runtime tuning," in *Proceedings of the 21st annual ACM symposium on User interface software and technology*, pp. 91–100, 2008.

[142] S. In, E. Roy Ayush, Krokos, K. Whitley, C. North, and Y. Yang, "Exploring organizational strategies in immersive computational notebooks,"

[143] M. Kraus, N. Weiler, D. Oelke, J. Kehrer, D. A. Keim, and J. Fuchs, "The Impact of Immersion on Cluster Identification Tasks," *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–1, 2019.

[144] K. Davidson, L. Lisle, I. A. Tahmid, K. Whitley, C. North, and D. A. Bowman, "Investigating professional analyst strategies in immersive space to think," *IEEE Transactions on Visualization and Computer Graphics*, 2024.

[145] W. Luo, M. O. Ellenberg, M. Satkowski, and R. Dachselt, "Documents in your hands: Exploring interaction techniques for spatial arrangement of augmented reality documents," in *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI'25). ACM, New York, NY, USA. doi*, vol. 10, 2025.

[146] M. Miller, D. Fürst, H. Hauptmann, and D. Keim, "Augmenting digital sheet music through visual analytics," *Computer Graphics Forum*, vol. 41, no. 3, pp. 247–259, 2022.

[147] J. Jo, S. L'Yi, B. Lee, and J. Seo, "TouchPivot: Blending WIMP & Post-WIMP Interfaces for Data Exploration on Tablet Devices," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, (Denver Colorado USA), pp. 2660–2671, ACM, May 2017.

[148] M. Whitlock, S. Smart, and D. A. Szafir, "Graphical perception for immersive analytics," in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 734–742, IEEE, 2020.

[149] A. Agarawala and R. Balakrishnan, "Keepin'it real: pushing the desktop metaphor with physics, piles and the pen," in *Proceedings of the SIGCHI conference on Human Factors in computing systems*, pp. 1283–1292, 2006.

[150] S. Lau, I. Drosos, J. M. Markel, and P. J. Guo, "The design space of computational notebooks: An analysis of 60 systems in academia and industry," in *2020 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC)*, pp. 1–11, IEEE, 2020.

[151] Y. Yang, W. Xia, F. Lekschas, C. Nobre, R. Krueger, and H. Pfister, "The Pattern is in the Details: An Evaluation of Interaction Techniques for Locating, Searching, and Contextualizing Details in Multivariate Matrix Visualizations," in *CHI Conference on Human Factors in Computing Systems*, pp. 1–15, Apr. 2022.

[152] S. Stoudt, V. N. Vásquez, and C. C. Martinez, "Principles for data analysis workflows," *PLOS Computational Biology*, vol. 17, no. 4, p. e1008770, 2021.

[153] L. Reimann and G. Kniesel-Wünsche, "An alternative to cells for selective execution of data science pipelines," in *2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE)*, IEEE, 2023.

[154] S. Sato and T. Nakamaru, "Multiverse notebook: Shifting data scientists to time travelers," *Proceedings of the ACM on Programming Languages*, 2024.

[155] S. In, E. Krokos, K. Whitley, C. North, and Y. Yang, "Investigating embodied data interactions for immersive computational notebooks,"

[156] B. Bach, N. Henry-Riche, T. Dwyer, T. Madhyastha, J.-D. Fekete, and T. Grabowski, "Small multipiles: Piling time to explore temporal patterns in dynamic networks," in *Computer Graphics Forum*, vol. 34, pp. 31–40, Wiley Online Library, 2015.

[157] K. A. Siek, Y. Rogers, and K. H. Connelly, "Fat finger worries: how older and younger users physically interact with pdas," in *IFIP Conference on Human-Computer Interaction*, pp. 267–280, Springer, 2005.

[158] H. Vasconcelos, M. Jörke, and R. Binns, "Explanations can reduce overreliance on ai systems during decision-making," in *Proceedings of the ACM on Human-Computer Interaction*, ACM, 2023.

[159] R. Chimera, "Value bars: an information visualization and navigation tool for multi-attribute listings," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 293–294, 1992.

[160] L. Pavanatto, F. Lu, C. North, and D. A. Bowman, "Multiple monitors or single canvas? evaluating window management and layout strategies on virtual displays," *IEEE Transactions on Visualization and Computer Graphics*, 2024.

[161] J. O. Wobbrock, M. R. Morris, and A. D. Wilson, "User-defined gestures for surface computing," in *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 1083–1092, 2009.

[162] E. A. Bier, M. C. Stone, K. Pier, W. Buxton, and T. D. DeRose, "Toolglass and magic lenses: the see-through interface," in *Seminal Graphics Papers: Pushing the Boundaries, Volume 2*, pp. 59–66, 2023.

[163] G. G. Robertson and J. D. Mackinlay, "The document lens," in *Proceedings of the 6th annual ACM symposium on User interface software and technology*, pp. 101–108, 1993.

[164] M. Sarkar and M. H. Brown, "Graphical fisheye views of graphs," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 83–91, 1992.

[165] J. J. Van Wijk and W. A. Nuij, "Smooth and efficient zooming and panning," in *IEEE Symposium on Information Visualization 2003 (IEEE Cat. No. 03TH8714)*, pp. 15–23, IEEE, 2003.

[166] A. Van Dam, D. H. Laidlaw, and R. M. Simpson, "Experiments in immersive virtual reality for scientific visualization," *Computers & Graphics*, vol. 26, no. 4, pp. 535–555, 2002.

[167] JupyterHub, "Computational notebook tool." https://jupyter.org/hub, 2025. Accessed: 2025-5-10.

# Appendices

# Appendix A

# Initial Explorations of Immerisve Computational Notebooks

# A.1 Informed Consent Form

**VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY**

**Consent to Take Part in a Research Study**

**Title of research study:** Immersive Computational Notebook in Virtual Reality (IRB# xx-xxx)

**Principal Investigator:** Dr Chris North and Dr. Yalong Yang
**Other study contact(s):**

- Sungwon In - sungwoni@vt.edu

**Key Information:** The following is a short summary of this study to help you decide whether to be a part of this study. More detailed information is listed later in this form.

One of the biggest concerns in the matter of using computational notebooks is navigation in the workplace. Although traditional computational notebooks provide a feasible layout for data science tasks when analysts want to compare multiple different results by modifying values of parameters, they have to scroll up and down many times, which causes a high overhead for context-switching.

A branch layout had been proposed to lower the cost, but was performed only in the desktop environment. Thus, this project aims to determine if using a virtual environment along with computational notebooks provides a novel method to perform data science tasks.

The procedure for the research study will require participants to attend only one session. The session will last for no longer than approximately 120 minutes. During the session, participants can expect to spend up to 15 minutes familiarizing themself with the Computational Notebook in VR application, up to 95 minutes conducting tasks that evaluate the application, and up to 10 minutes completing the questionnaire.

**Detailed Information:** The following is more detailed information about this study in addition to the information listed above.

### Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Sungwon In (sungwoni@vt.edu).

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research

### How many people will be studied?

We plan to include up to ten people in this research study.

## A.2 Pre-Study Questionnaire



# Background Question

* Indicates required question

ID number (the three digits number provided by the conductor) *

Your answer

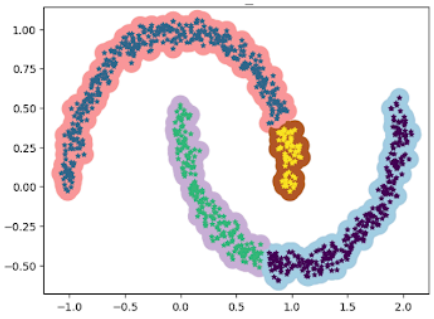
**DBSCAN** (**D**ensity-**B**ased **S**patial **C**lustering of **A**pplications with **N**oise)

Choose one parameter that you can fine-tun for DBSCAN? *

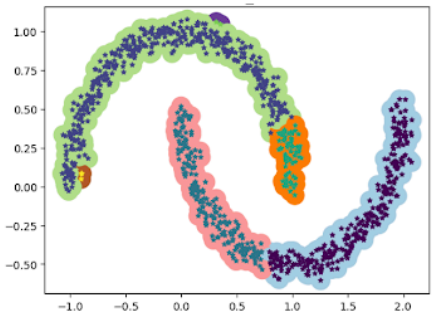
- ◯ eps (epsilon)
- ◯ Distance between two dots
- ◯ Number of clusters

Pre-fill responses, then click "Get link"

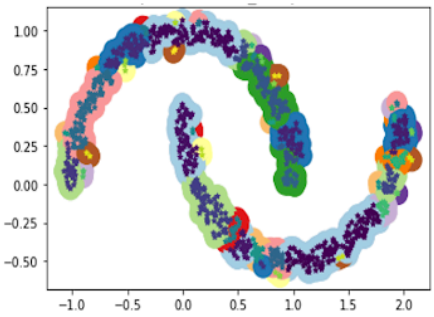
Which of the following DBSCAN-grouped scatter plot provides the "four distinct" groups? *



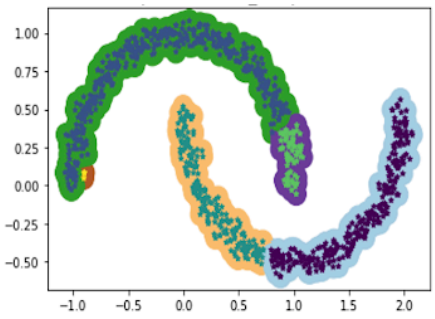

(a)




(b)




(c)



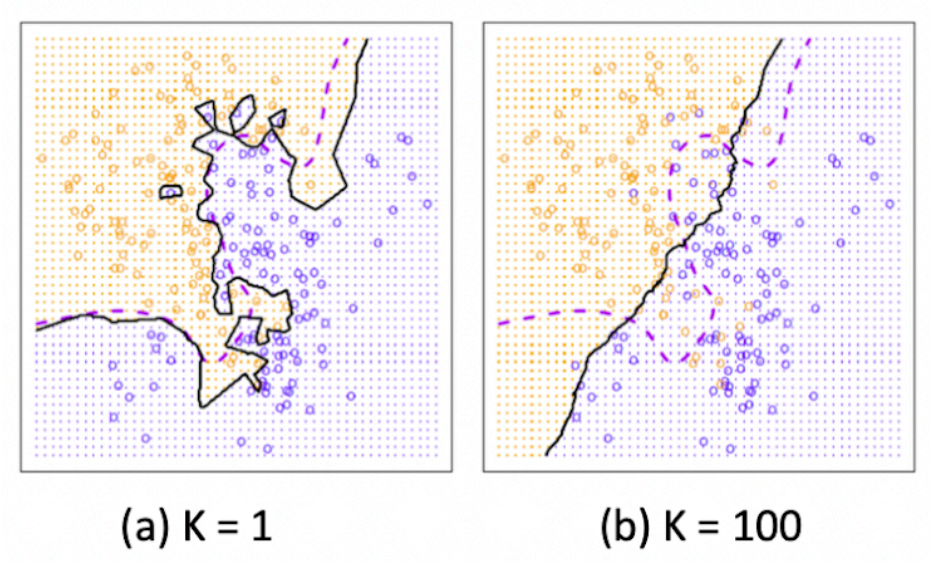

(d)

- ◯ (a)
- ◯ (b)
- ◯ (c)
- ◯ (d)

**KNN** (**K-N**earest **N**eighbors)

Pre-fill responses, then click "Get link"

Which of the following KNN-grouped scatter plot provides "two distinct" groups? * (ignore dotted line)




- (a)
- (b)

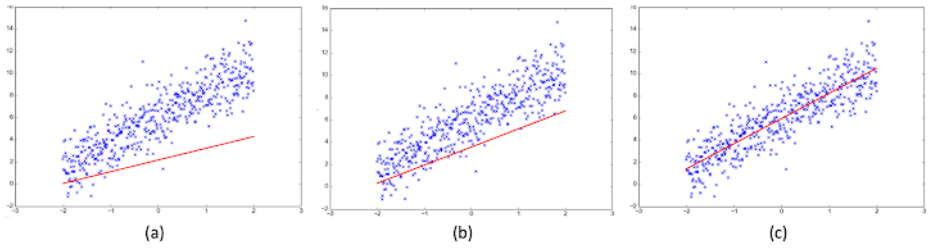
Choose one parameter that you can fine-tun for KNN *

- Metric
- Number of neighbors
- Kernel size

**Linear Regression**

Pre-fill responses, then click "Get link"

Which option illustrates the "best" prediction? *




- (a)
- (b)
- (c)

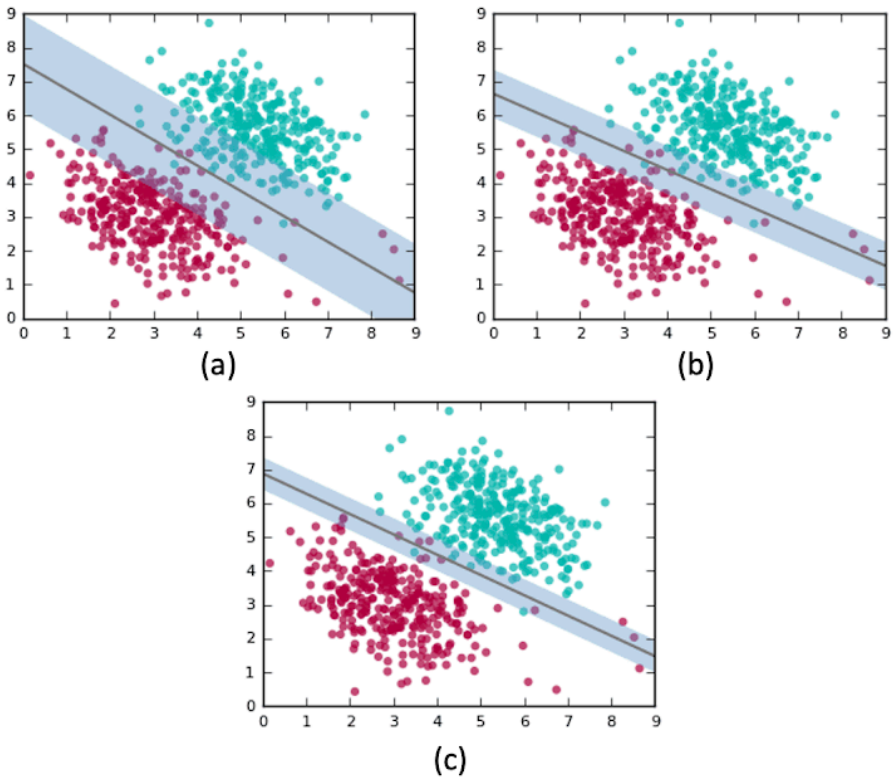
Choose one parameter that you can fine-tune for Linear Regression *

- Padding size
- Distance between two dots
- Regularization

**SVM** (**S**upport **V**ector **M**achine)

Pre-fill responses, then click "Get link"

Which of the following SVM-grouped scatter plot provides the "smallest" Maximum-margin? *




- (a)
- (b)
- (c)

Choose one parameter that you can fine-tun for SVM *

- Metric
- Gamma
- Distance between two dots

Pre-fill responses, then click "Get link"

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Pre-fill responses, then click "Get link"

Pre-fill responses, then click "Get link"

## A.3 Post-Study Questionnaire



# VR: Branch

* Indicates required question

ID Number (the three digits number provided by the conductor) *

Your answer

Do you have experience with virtual reality? *

- ◯ Yes
- ◯ No

If yes, how frequently do you use it in a week? *

- ◯ 1 - 2
- ◯ 3 - 5
- ◯ 5 - 7
- ◯ More than 7
- ◯ None of these

Pre-fill responses, then click "Get link"

How mentally demanding was the task? *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very Low | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very High |

How physically demanding was the task? *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very Low | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very High |

How hurried or rushed was the pace of the task? *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very Low | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very High |

How successful were you in accomplishing what you were asked to do? *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very much |

How hard did you have to work to accomplish your level of performance? *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Hard |

Pre-fill responses, then click "Get link"

How insecure, discouraged, irritated, stressed, and annoyed were you? *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I think that I would like to use this system frequently *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I found the system unnecessarily complex *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I thought the system was easy to use *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I think that I would need the support of a technical person to be able to use this system *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

Pre-fill responses, then click "Get link"

I found the various functions in this system were well integrated *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I would imagine that most people would learn to use this system very quickly *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I found the system very cumbersome to use *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I felt very confident using the system *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

I needed to learn a lot of things before I could get going with this system *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

Pre-fill responses, then click "Get link"

I found it impressive *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not at all | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Impressive |

I liked this interaction *

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not so much | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Very Much |

What do you like about this interaction? *
(Let the conductor write this and have a rest!)

Your answer

What do you not like about this interaction? *
(Let the conductor write this and have a rest!)

Your answer

Get link

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Pre-fill responses, then click "Get link"

# A.4 IRB Approval Letter

**Division of Scholarly Integrity and Research Compliance**
Institutional Review Board
North End Center, Suite 4120 (MC 0497)
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-3732
irb@vt.edu
http://www.research.vt.edu/sirc/hrpp

VIRGINIA TECH

**MEMORANDUM**

**DATE:** May 23, 2023

**TO:** Yalong Yang, Christopher L North, Sungwon In

**FROM:** Virginia Tech Institutional Review Board (FWA00000572)

**PROTOCOL TITLE:** Immersive Analytics: Computational Notebook in VR

**IRB NUMBER:** **23-527**

Effective May 23, 2023, the Virginia Tech Human Research Protection Program (HRPP) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104(d) category (ies) 2(ii).

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit an amendment to the HRPP for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

**PROTOCOL INFORMATION:**

| | |
|---|---|
| Determined As: | **Exempt, under 45 CFR 46.104(d) category(ies) 2(ii)** |
| Protocol Determination Date: | **May 23, 2023** |

**ASSOCIATED FUNDING:**

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

| Date* | OSP Number | Sponsor | Grant Comparison Conducted? |
|---|---|---|---|
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this protocol is to cover any other grant proposals, please contact the HRPP office (irb@vt.edu) immediately.

# Appendix B

# Embodied Data Transformation

# B.1 Informed Consent Form

**VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY**

**Consent to Take Part in a Research Study**

**Title of research study:** Data Transformation in Virtual Reality (IRB# 22-443)

**Principal Investigator:** Dr. Yalong Yang, yalongyang@vt.edu
**Other study contact(s):**

- Sungwon In - sungwoni@vt.edu

**Key Information:** The following is a short summary of this study to help you decide whether to be a part of this study. More detailed information is listed later in this form.

VR technology opened a new dimension of immersive aesthetics to the data visualization. However, this immersiveness provided by wearing a headset often disconnects its user from the workflow. Data wrangling should be done before visualizing the data without the headset.

In order to resolve these disconnections, entire work should be done by wearing a headset. The system should have data wrangling function to have natural workflow. This project aims to determine if using a virtual environment along with data transformation provides a novel and viable method to visualize data without disconnection.

The procedure for the research study will require participants to attend only one session. The session will last for no longer than approximately 90 minutes. During the session, participants can expect to spend up to 15 minutes familiarizing themself with the Data Transformation in VR application, up to 55 minutes conducting tasks that evaluate the application, and up to 10 minutes completing the questionnaire.

**Detailed Information:** The following is more detailed information about this study in addition to the information listed above.

### Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Sungwon In (sungwoni@vt.edu).

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research

### How many people will be studied?

We plan to include up to ten people in this research study.

We plan to include about ten people at this location out of ten people in the entire study nationally.

# B.2 Pre-Study Questionnaire



## Background Question

* Indicates required question

1. ID number (the three digits number provided by the conductor) *

2. Data transformation does NOT involve *

   *Mark only one oval.*

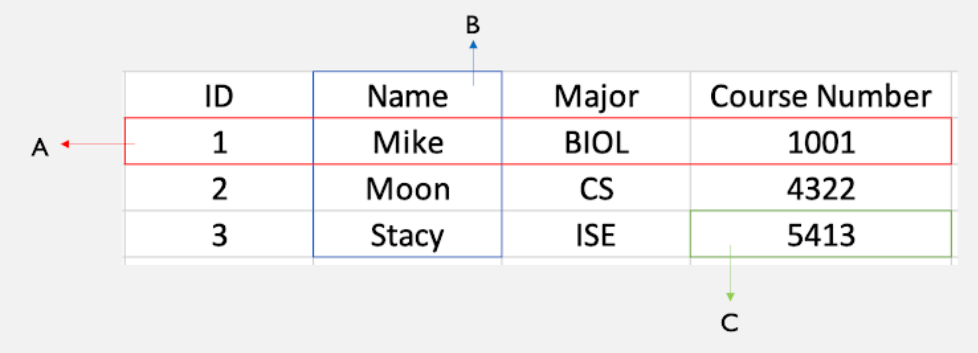
   - ◯ Data editing
   - ◯ Data analyzing
   - ◯ Data wrangling

3. What is merge in terms of data science? *

   *Mark only one oval.*

   - ◯ Combine 2 data table into 1 data table
   - ◯ Extract certain data
   - ◯ Filter data

4. In the following figure, what is a 'cell'? *




| ID | Name | Major | Course Number |
|---|---|---|---|
| 1 | Mike | BIOL | 1001 |
| 2 | Moon | CS | 4322 |
| 3 | Stacy | ISE | 5413 |

*Mark only one oval.*

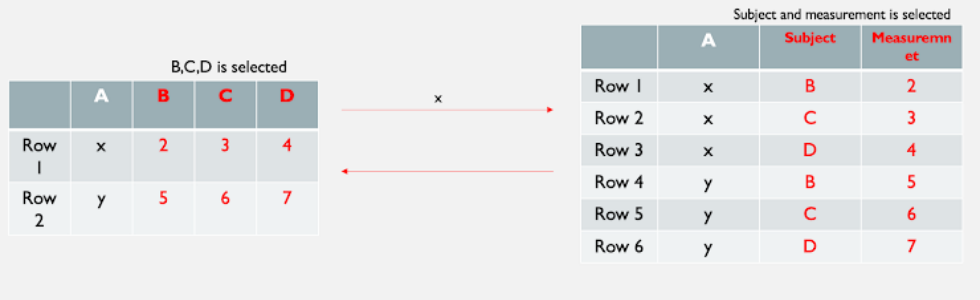
- A
- B
- C

5. When you 'group' data, the grouped column summarizes the existing data in, EXCLUDING: *

*Mark only one oval.*

- Average
- Sum
- Substract
- Median

6. 'x' on the red arrow is one of the data transformation functions; what function has been performed in 'x'? *




*Mark only one oval.*

- ◯ Long to wide
- ◯ Wide to long
- ◯ Ungroup
- ◯ Group

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# B.3 Post-Study Questionnaire



## Embodied Data Transformation

* Indicates required question

1. ID Number (the three digits number provided by the conductor) *

2. Do you have experience with virtual reality? *

   *Mark only one oval.*

   - ◯ Yes
   - ◯ No

3. If yes, how frequently do you use it in a week? *

   *Mark only one oval.*

   - ◯ 1 - 2
   - ◯ 3 - 5
   - ◯ 5 - 7
   - ◯ More than 7
   - ◯ None of these

4. Please write down the operation you use in order as much as you can. *
   (type of operation: extract / delete / sort / filter / merge / long & wide / group)

Untitled Section

5. How mentally demanding was the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

6. How physically demanding was the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

7. How hurried or rushed was the pace of the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

8. How successful were you in accomplishing what you were asked to do? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very much |

9. How hard did you have to work to accomplish your level of performance? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Hard |

10. How insecure, discouraged, irritated, stressed, and annoyed were you? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

11. I think that I would like to use this system frequently *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

12. I found the system unnecessarily complex *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

13. I thought the system was easy to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

14. I think that I would need the support of a technical person to be able to use this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

15. I found the various functions in this system were well integrated *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

16. I would imagine that most people would learn to use this system very quickly *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

17. I found the system very cumbersome to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

18. I felt very confident using the system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

19. I needed to learn a lot of things before I could get going with this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

20. I found it impressive *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Impressive |

21. I liked this interaction *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

22. What do you like about this interaction? *
(Let the conductor write this and have a rest!)

23. What do you not like about this interaction? *
(Let the conductor write this and have a rest!)

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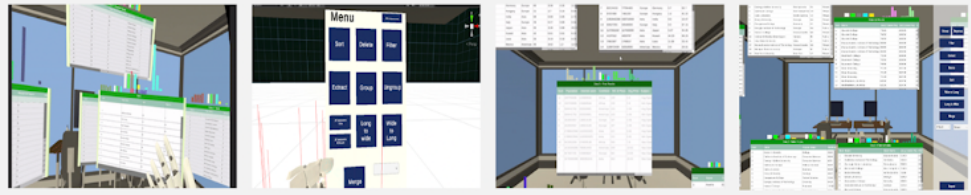
# Final Survey

Lorem ipsum dolor sit amet, consectetur adipiscing elit.

* Indicates required question

1. ID Number (the three digits number provided by the conductor) *

2. Please rank the following 4 interactions in the order of your enjoyment where: 1 is most enjoyable, and 4 is least enjoyable. *




*Mark only one oval per row.*

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Monitor: WIMP** | ◯ | ◯ | ◯ | ◯ |
| **Monitor: 2D** | ◯ | ◯ | ◯ | ◯ |
| **VR: WIMP** | ◯ | ◯ | ◯ | ◯ |
| **VR: 3D Interaction** | ◯ | ◯ | ◯ | ◯ |

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# B.4 IRB Approval Letter

**Division of Scholarly Integrity and Research Compliance**
Institutional Review Board
North End Center, Suite 4120 (MC 0497)
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-3732
irb@vt.edu
http://www.research.vt.edu/sirc/hrpp

**MEMORANDUM**

**DATE:** June 10, 2022

**TO:** Yalong Yang, Sungwon In

**FROM:** Virginia Tech Institutional Review Board (FWA00000572)

**PROTOCOL TITLE:** Data Transformation in Virtual Reality

**IRB NUMBER:** **22-443**

Effective June 10, 2022, the Virginia Tech Human Research Protection Program (HRPP) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104(d) category (ies) 2(ii),3(i)(B).

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit an amendment to the HRPP for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

**PROTOCOL INFORMATION:**

| | |
|---|---|
| Determined As: | **Exempt, under 45 CFR 46.104(d) category(ies) 2(ii),3(i)(B)** |
| Protocol Determination Date: | **June 10, 2022** |

**ASSOCIATED FUNDING:**

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

| Date* | OSP Number | Sponsor | Grant Comparison Conducted? |
|---|---|---|---|
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this protocol is to cover any other grant proposals, please contact the HRPP office (irb@vt.edu) immediately.

# Appendix C

# ICoN: Immersive Computational Notebook for Data Science

# C.1 Informed Consent Form: First User Study

**VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY**

**Consent to Take Part in a Research Study**

**Title of research study:** Immersive Computational Notebook: Comprehensive System for Data Science (IRB# 24-151)

**Principal Investigator:** Dr. Chris North, north@cs.vt.edu
**Other study contact(s):**

- Sungwon In - sungwoni@vt.edu

**Key Information:** The following is a short summary of this study to help you decide whether to be a part of this study. More detailed information is listed later in this form.

One of the biggest concerns in the matter of using computational notebooks is navigation in the workplace. Although traditional computational notebooks provide a feasible layout for data science tasks when analysts want to compare multiple different results by modifying values of parameters, they have to scroll up and down many times, which causes a high overhead for context-switching.

A branch layout had been proposed to lower the cost, but was performed only in the desktop environment. Thus, this project aims to determine if using a virtual environment along with computational notebooks provides a novel method to perform data science tasks.

The procedure for the research study will require participants to attend only one session. The session will last for no longer than approximately 60 minutes. During the session, participants can expect to spend up to 15 minutes familiarizing themself with the Computational Notebook in VR application, up to 25 minutes conducting tasks that evaluate the application, and up to 5 minutes completing the questionnaire.

**Detailed Information:** The following is more detailed information about this study in addition to the information listed above.

### Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Sungwon In (sungwoni@vt.edu).

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research

### How many people will be studied?

We plan to include up to ten people in this research study.

# C.2 Post-Study Questionnaire: First Study



## ICoN: Usability tests

* Indicates required question

1. ID Number (the three digits number provided by the conductor) *

2. Do you have experience with virtual reality? *

   *Mark only one oval.*

   - ◯ Yes
   - ◯ No

3. If yes, how frequently do you use it in a week? *

   *Mark only one oval.*

   - ◯ 1 - 2
   - ◯ 3 - 5
   - ◯ 5 - 7
   - ◯ More than 7
   - ◯ None of these

Untitled Section

4. How mentally demanding was the task? *

   *Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

5. How physically demanding was the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

6. How hurried or rushed was the pace of the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

7. How successful were you in accomplishing what you were asked to do? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very much |

8. How hard did you have to work to accomplish your level of performance? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Hard |

9. How insecure, discouraged, irritated, stressed, and annoyed were you? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

10. I think that I would like to use this system frequently *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

11. I found the system unnecessarily complex *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

12. I thought the system was easy to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

13. I think that I would need the support of a technical person to be able to use this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

14. I found the various functions in this system were well integrated *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

15. I would imagine that most people would learn to use this system very quickly *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

16. I found the system very cumbersome to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

17. I felt very confident using the system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

18. I needed to learn a lot of things before I could get going with this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | |
|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

19. I found it impressive *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Impressive |

20. How was the experience in DataDive compared to previous experience (e.g. Jupyter Notebook) to perform editing data, and visualizing those? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Effective |

21. I liked this interaction *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

22. What do you like about this interaction? *
(Let the conductor write this and have a rest!)

23. What do you not like about this interaction? *
(Let the conductor write this and have a rest!)

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# C.3 Informed Consent Form: Second User Study

**VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY**

**Consent to Take Part in a Research Study**

**Title of research study:** Immersive Computational Notebook: Comprehensive System for Data Science (IRB# 24-151)

**Principal Investigator:** Dr. Chris North, north@cs.vt.edu
**Other study contact(s):**

- Sungwon In - sungwoni@vt.edu

**Key Information:** The following is a short summary of this study to help you decide whether to be a part of this study. More detailed information is listed later in this form.

One of the biggest concerns in the matter of using computational notebooks is navigation in the workplace. Although traditional computational notebooks provide a feasible layout for data science tasks when analysts want to compare multiple different results by modifying values of parameters, they have to scroll up and down many times, which causes a high overhead for context-switching.

A branch layout had been proposed to lower the cost, but was performed only in the desktop environment. Thus, this project aims to determine if using a virtual environment along with computational notebooks provides a novel method to perform data science tasks.

The procedure for the research study will require participants to attend only one session. The session will last for no longer than approximately 90 minutes. During the session, participants can expect to spend up to 30 minutes familiarizing themself with the Computational Notebook in VR application, up to 50 minutes conducting tasks that evaluate the application, and up to 5 minutes completing the questionnaire.

**Detailed Information:** The following is more detailed information about this study in addition to the information listed above.

### Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Sungwon In (sungwoni@vt.edu).

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research

### How many people will be studied?

We plan to include up to ten people in this research study.

# C.4 Post-Study Questionnaire: Second Study



## ICoN: Desktop - Exo

* Indicates required question

1. ID Number (the three digits number provided by the conductor) *

2. Do you have experience with virtual reality? *

   *Mark only one oval.*

   - ◯ Yes
   - ◯ No

3. If yes, how frequently do you use it in a week? *

   *Mark only one oval.*

   - ◯ 1 - 2
   - ◯ 3 - 5
   - ◯ 5 - 7
   - ◯ More than 7
   - ◯ None of these

### Untitled Section

4. How mentally demanding was the task? *

   *Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

5. How physically demanding was the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

6. How hurried or rushed was the pace of the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

7. How successful were you in accomplishing what you were asked to do? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very much |

8. How hard did you have to work to accomplish your level of performance? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Hard |

9. How insecure, discouraged, irritated, stressed, and annoyed were you? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

10. I think that I would like to use this system frequently *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

11. I found the system unnecessarily complex *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

12. I thought the system was easy to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

13. I think that I would need the support of a technical person to be able to use this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

14. I found the various functions in this system were well integrated *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

15. I would imagine that most people would learn to use this system very quickly *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

16. I found the system very cumbersome to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

17. I felt very confident using the system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

18. I needed to learn a lot of things before I could get going with this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

19. I found it impressive *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Impressive |

20. I liked this interaction *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

21. What do you like about this interaction? *
(Let the conductor write this and have a rest!)
1. Interaction consistency?
2. Intuitivness?
3. Efforts?
4. Memorability?

22. What do you not like about this interaction? *
(Let the conductor write this and have a rest!)

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# C.5 IRB Approval Letter

**Division of Scholarly Integrity and Research Compliance**
Institutional Review Board
North End Center, Suite 4120 (MC 0497)
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-3732
irb@vt.edu
http://www.research.vt.edu/sirc/hrpp

VIRGINIA TECH

**MEMORANDUM**

**DATE:** February 15, 2024

**TO:** Christopher L North, Sungwon In

**FROM:** Virginia Tech Institutional Review Board (FWA00000572)

**PROTOCOL TITLE:** Immersive Computational Notebook: Comprehensive System for Data Science

**IRB NUMBER:** **24-151**

Effective February 15, 2024, the Virginia Tech Human Research Protection Program (HRPP) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104 (d) category(ies) 2(i),3(i)(A).

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit an amendment to the HRPP for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

**PROTOCOL INFORMATION:**

| | |
|---|---|
| Determined As: | **Exempt, under 45 CFR 46.104(d) category(ies) 2(i),3(i)(A)** |
| Protocol Determination Date: | **February 15, 2024** |

**ASSOCIATED FUNDING:**

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

**SPECIAL INSTRUCTIONS:**

***Please note: The HRPP office has stopped stamping documents for Exempt protocols. It is your responsibility to maintain these documents and make current versions available on request.

| Date* | OSP Number | Sponsor | Grant Comparison Conducted? |
|---|---|---|---|
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this protocol is to cover any other grant proposals, please contact the HRPP office (irb@vt.edu) immediately.

# Appendix D

# Exploring Organizational Strategies in ICoN

# D.1 Informed Consent Form

**VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY**

**Consent to Take Part in a Research Study**

**Title of research study:** Immersive Computational Notebook: Comprehensive System for Data Science (IRB# 24-151)

**Principal Investigator:** Dr. Chris North, north@cs.vt.edu

**Other study contact(s):**

- Sungwon In - sungwoni@vt.edu
- Ayush Roy – ayushroy24@vt.edu

**Key Information:** The following is a short summary of this study to help you decide whether to be a part of this study. More detailed information is listed later in this form.

One of the biggest concerns in the matter of using computational notebooks is navigation in the workplace. Although traditional computational notebooks provide a feasible layout for data science tasks when analysts want to compare multiple different results by modifying values of parameters, they have to scroll up and down many times, which causes a high overhead for context-switching.

A branch layout had been proposed to lower the cost, but was performed only in the desktop environment. Thus, this project aims to determine if using a virtual environment along with computational notebooks provides a novel method to perform data science tasks.

The procedure for the research study will require participants to attend only one session. The session will last for no longer than approximately 90 minutes. During the session, participants can expect to spend up to 30 minutes familiarizing themself with the Computational Notebook in VR application, up to 50 minutes conducting tasks that evaluate the application, and up to 5 minutes completing the questionnaire.

**Detailed Information:** The following is more detailed information about this study in addition to the information listed above.

### Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Sungwon In (sungwoni@vt.edu) or Ayush Roy (ayushroy24@vt.edu).

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research

# D.2 Post-Study Questionnaire



## ICoN Organization

* Indicates required question

1. ID Number (the three digits number provided by the conductor) *

2. Do you have experience with virtual reality? *

   *Mark only one oval.*

   - Yes
   - No

3. If yes, how frequently do you use it in a week? *

   *Mark only one oval.*

   - 1 - 2
   - 3 - 5
   - 5 - 7
   - More than 7
   - None of these

Untitled Section

4. How mentally demanding was the task? *

   *Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

5. How physically demanding was the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

6. How hurried or rushed was the pace of the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

7. How successful were you in accomplishing what you were asked to do? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very much |

8. How hard did you have to work to accomplish your level of performance? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Hard |

9. How insecure, discouraged, irritated, stressed, and annoyed were you? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

10. I think that I would like to use this system frequently *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

11. I found the system unnecessarily complex *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

12. I thought the system was easy to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

13. I think that I would need the support of a technical person to be able to use this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

14. I found the various functions in this system were well integrated *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

15. I would imagine that most people would learn to use this system very quickly *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

16. I found the system very cumbersome to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

17. I felt very confident using the system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

18. I needed to learn a lot of things before I could get going with this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

19. I found it impressive *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Impressive |

20. I liked this interaction *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

21. What do you like about this interaction? *
(Let the conductor write this and have a rest!)

22. What do you not like about this interaction? *
(Let the conductor write this and have a rest!)

23. How do you feel when you are organizing documents?

24. How do you feel when you need to manage your workspace and handle the contents around you compare to larger notebooks and smaller notebook? (Does the navigation were hard? any suggestion on managing all these docuements?)

This content is neither created nor endorsed by Google.

# Appendix E

# Embodied Organizational Guidance for ICoN

# E.1 Informed Consent Form

**VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY**

**Consent to Take Part in a Research Study**

**Title of research study:** Immersive Computational Notebook: Comprehensive System for Data Science (IRB# 24-151)

**Principal Investigator:** Dr. Chris North, north@cs.vt.edu
**Other study contact(s):**

- Sungwon In - sungwoni@vt.edu

**Key Information:** The following is a short summary of this study to help you decide whether to be a part of this study. More detailed information is listed later in this form.

Managing a large number of computational notebooks for complex data science tasks requires efficient interaction methods. To address this challenge, we developed templates, incorporating both linear and non-linear execution orders, which reflect common organizational patterns observed in computational notebooks when placement flexibility was given. We envision these templates facilitate the process of structuring organizations in immersive computational notebooks.

However, applying these templates requires identifying related cells, a process that becomes increasingly difficult when navigating large immersive workspaces. Manually locating relevant cells can be time-consuming and cognitively demanding. To overcome this, we envision an AI-assisted recommendation system that suggests related cells, optimizing template application and reducing the effort needed for manual organization.

This project aims to evaluate whether templates and AI assistance provide an effective method for building structured and intuitive workflows within immersive computational notebooks.

The procedure for the research study will require participants to attend only one session. The session will last for no longer than approximately 90 minutes. During the session, participants can expect to spend up to 30 minutes familiarizing themself with the Computational Notebook in VR application, up to 50 minutes conducting tasks that evaluate the application, and up to 5 minutes completing the questionnaire.

**Detailed Information:** The following is more detailed information about this study in addition to the information listed above.

### Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team at Sungwon In (sungwoni@vt.edu).

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject

# E.2 Post-Study Questionnaire



## ICoN Template

* Indicates required question

1. ID Number (the three digits number provided by the conductor) *

2. Do you have experience with virtual reality? *

   *Mark only one oval.*

   - ◯ Yes
   - ◯ No

3. If yes, how frequently do you use it in a week? *

   *Mark only one oval.*

   - ◯ 1 - 2
   - ◯ 3 - 5
   - ◯ 5 - 7
   - ◯ More than 7
   - ◯ None of these

### Untitled Section

4. How mentally demanding was the task? *

   *Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

5. How physically demanding was the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

6. How hurried or rushed was the pace of the task? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Very | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very High |

7. How successful were you in accomplishing what you were asked to do? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very much |

8. How hard did you have to work to accomplish your level of performance? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Hard |

9. How insecure, discouraged, irritated, stressed, and annoyed were you? *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

10. I think that I would like to use this system frequently *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

11. I found the system unnecessarily complex *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

12. I thought the system was easy to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

13. I think that I would need the support of a technical person to be able to use this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

14. I found the various functions in this system were well integrated *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

15. I would imagine that most people would learn to use this system very quickly *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

16. I found the system very cumbersome to use *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

17. I felt very confident using the system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

18. I needed to learn a lot of things before I could get going with this system *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

19. I found it impressive *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Impressive |

20. I liked this interaction *

*Mark only one oval.*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| Not | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | ◯ | Very Much |

21. What do you like about this interaction? *
(Let the conductor write this and have a rest!)

22. What do you not like about this interaction? *
(Let the conductor write this and have a rest!)

23. How do you feel when you are organizing documents?

24. How do you feel the process of identifying the related cells?

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