Comparing the Quality of Business Decisions Supported by Alternative Visualisation Platforms

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Abstract - **Aroaro is a mixed-reality, multi-user platform, which can be deployed on different virtual reality and augmented reality devices. In Aroaro, users can experience data visualisation. This paper presents our proposed approach to network data visualisation in a business context, which assumes a business unit is tasked with problems that need to reveal information found in a network data set. Aroaro provides users with a novel way to visualise the network in a mixed-reality immersive environment while helping decision-makers retrieve the analytics toolbox that supports their tasks. We report on experimentation with subjects who participated in lab sessions to qualitatively compare aspects of their decisions performed on two visualisation platforms. Our objective at this stage is to infer how and when our immersive, virtual reality visualisation tool turns out to be superior to alternative 2D flat-screen visualisation facilities.**

Keywords - augmented reality; data visualisation; immersive analytics; multi-user; mixed-reality platform; network data set; virtual reality

I. INTRODUCTION

Data visualisation has become important for businesses as decisions need to be informed by increasingly larger and more complex data sets. Coupled with data analytics, data visualisation may enhance decision makers' understanding of relations and features of the data that would have remained hidden otherwise.

From the different approaches to visualising data, this paper draws on visualisations done in a flat screen for charts, graphs and figures as well as a virtual reality environment that affords an immersive sensory experience.

Businesses are experiencing a growing demand to obtain, extract and process information contained in complex network structures. Social networks, seen as a collection of individuals and their relationships, exemplify organisations where data-oriented businesses find rich sources of information. Conventional data sets, known as tabular data sets, may convey information about individual or aggregate members of a group, but no explicit information about the relationships among its members. In contrast, a network data set (more appropriately known as a graph data set), not only identifies each member (i.e., a node), but it also explicitly identifies direct bilateral relationships within the set (i.e., links).

The problem presented here assumes that a particular business organisation has access to a network data set, which may be its own or a third party's. Analysts are tasked with problems that demand exploration of the network structure and its underlying connectivity. They need to make decisions in a particular context that uses the network data set. For instance, assuming the network data set describes a network of individuals, such as an Internet-based social network, let us suppose decision-makers need to establish which subjects are the most important in helping the business propagate a message. A subject's importance can be preestablished applying quantitative criteria to the information contained in the data. In a multi-criteria context, decision-makers may face several options. Given the complex structure of a network, the decision-maker may use a visualisation tool that will provide a broader, sensorial background that can be jointly explored with other analysts.

Our approach contemplates decision-makers facing two visualisation options: data displayed on a 2D interface – such as a computer screen - or data displayed on an immersive virtual reality environment. Our research efforts are focused on determining the problem types that render one method more effective than the other in the context of querying a network data set assisted by a visualisation tool.

The paper unfolds as follows. Section II provides a succinct overview of the growing field of Immersive Analytics. Section III discusses our newly introduced techniques for business decision-making in the context of network data analysis, which relies on the utilisation of two visualisation platforms. In Section IV, we discuss the experimental methodology employed and explain the analytical concepts used in our exploration of the problem. Then, in section V, we present observations and discuss results. In section VI we present the conclusions.

II. LITERATURE REVIEW AND LIMITATIONS OF CURRENT TECHNOLOGY

The U.S. National Research Council defines Network Science as the study of network representations of physical, biological, and social phenomena leading to predictive models of these phenomena. The tools used to understand network-based decision-making seek to help the analyst to discover principles, relations and other aspects governing network behaviour. Such discovery may be boosted by the combination of advanced visualisation technology and new ways to represent abstract data.

Figure 1, by DB-Engines.com, shows the growth in popularity for different database categories, with network (graph) databases showing a sustained increase in popularity over the last eight years. Network databases offer efficient, flexible and convenient ways to find patterns within the data contained in a network dataset. Complex problems can be easily modelled when a network database is used to store, retrieve, and process network data sets.

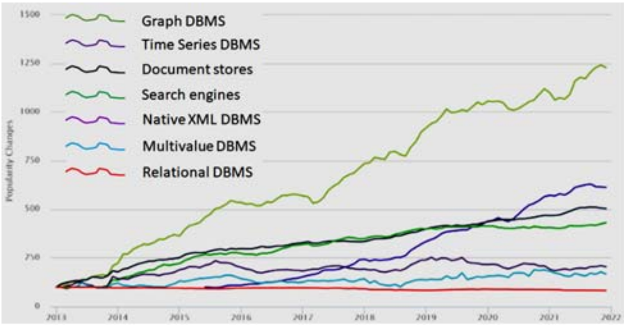

Figure 1. Historical trend of the database categories' popularity.1 (taken from DB-Engines.com)

These affordances and the growth in popularity of network databases have motivated the work presented here where we aim to support businesses in understanding the data available through visualisation. Given the strategic importance of network information for businesses, visualisation methods allow network data to be used in decision-making and facilitate the interpretation of analytics applied to network data

According to Dwyer et al. [1], Immersive Analytics (IA) is "the use of engaging, embodied analysis tools to support data understanding and decision-making." Immersive analytics builds upon several features such as data visualisation, visual analytics, virtual reality, computer graphics, human-computer interaction to support data understanding, and individual or collaborative decision-making. IA is a new technology that uses head-mounted Virtual Reality (VR) and Augmented Reality, or hand-held equipment to provide new kinds of display and interaction technologies such as sensor technologies and machine learning [2].

The literature on collaborative visual analysis of abstract data in immersive environments is scarce. Existing studies focus on virtual reality and augmented reality technologies applied to immersive environments for visualisation. We focus here on developments that have adopted Head-Mounted Devices (HMDs). HDMs and other equipment allow the user to get immersed in a, often, previously unimagined non-physical landscape. Once in there, a subject may want to analyse data taking advantage of the richer visualisation space. Kwon et al. [3], investigating the effectiveness of graph visualisation, report a superior performance of 3D visualisation with an Oculus Rift over 2D graph visualisation. Different authors exploring collaboration in information visualisation highlight its importance for data visualisation, in general, and big and complex data, in particular [4], [5], [6].

Noting the increasing adoption of HMDs due to their technical advancements, Cordeil et al. [7] compare a centralised automatic virtual environment or CAVE and the environment afforded by an HMD. The comparison is based on three criteria: resolution, presence, and freedom of movement. [7] Focuses on immersive collaborative analysis of network connectivity. Invited subjects were asked to perform tasks while visualising a network. The tasks consisted of counting the number of triangles and finding the shortest path between given nodes and were to be performed collaboratively by two subjects. HMDs were found to allow users to achieve their tasks faster than when the CAVE was used, and there were no notable differences in terms of accuracy and communication.

III. PROPOSED NEW TECHNIQUES

Networks visualisation provides an alternative way to discover, extract and classify new patterns in network data sets. In the present study, a network data set was used as the object to be displayed and visualised by the subjects on both a commercial open-source network analysis and visualisation software package, and on an immersive virtual reality platform. The former is Gephi, whereas the latter is **Aroaro**, a tool developed by the researchers. Gephi uses a “visualise-and-manipulate paradigm” that allows the user to explore, analyze, spatialize, filter, cluster, manipulate, and export “all types of networks” (www.gephi.org/about). Gephi users can visualise a network data set on a 2D flat screen as illustrated in Figure 1. In contrast, Aroaro, an immersive virtual environment, allows a user to experience virtual and augmented reality by wearing a device in such a way that their sight and hearing engage with a representation of the world that is totally created by the installed software or an altered view of the real world.

Our mixed-reality environment, Aroaro, affords an interpretation of a network data set that feels like an exploration journey of the nodes and links suspended right in front of the user. Aroaro has a facility that allows the user to display the connectivity information inherent to a network data set as a graph that “floats on the virtual space”. Figure 2 presents a picture captured from a screen projection of the same image a user of our VR Aroaro system is simultaneously experiencing in her HDM.

[1] According to DB-Engines website: “*In the ranking of each month the best three systems per category are chosen and the average of their ranking scores is calculated. In order to allow comparisons, the initial value is normalized to 100*.”

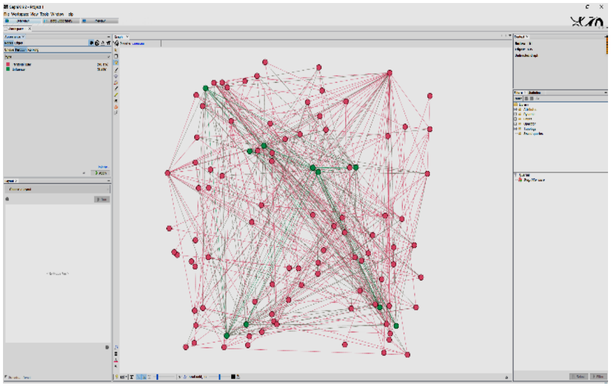

Figure 2. Sample network visualised in Gephi

Figure 3 shows two visualisations. In the first, a node is shown just as a decision maker would see it in Aroaro's VR space by means of an HMD. Users could select the information to be displayed associated with each node. The lower figure shows how a node is viewed by a decision maker that uses Gephi. Both figures highlight the viewed node's neighbours. We argue that displaying the data on an immersive graphical network representation - such as Aroaro - enriches not only the interaction but the quality of the analysis, with potential for better decisions.

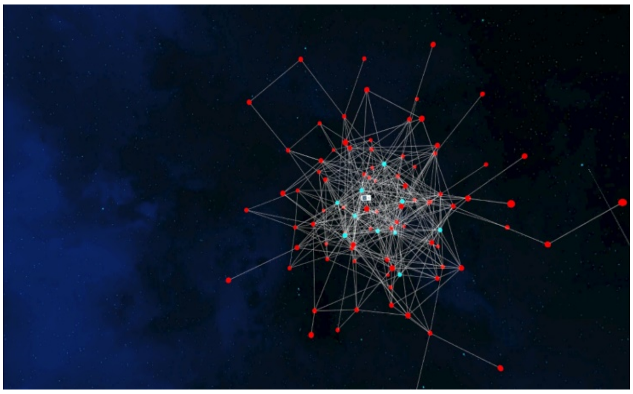

Figure 3. Sample network in Aroaro's VR space

Introducing IA to Aroaro offers opportunities beyond traditional analytics such as those identified in [8]: situated analytics, embodied data exploration, collaboration, spatial immersion, multi-sensory presentation and engagement. Aroaro takes on some of these opportunities as follows:

1. Aroaro is a multi-user environment that incorporates collaboration that can happen either synchronously or asynchronously. A team of decision makers can meet in Aroaro from geographically distant places. If the session happens with all members being simultaneously in the virtual environment, then interaction will occur in a synchronous manner. Decision makers can also rely on individual immersive analytics and leave their annotations on virtual or real objects of interest so that other team members can continue their tasks later.

2. Aroaro's virtual reality provides a user with total *spatial immersion* where users can gain better understanding of the data. User interaction with network data happens as the user "flies into the network", while being able to explore any object with a sense of unconstrained space. The environment is a full 3D visualisation of Aroaro's interpretation of data contained in a network data set.

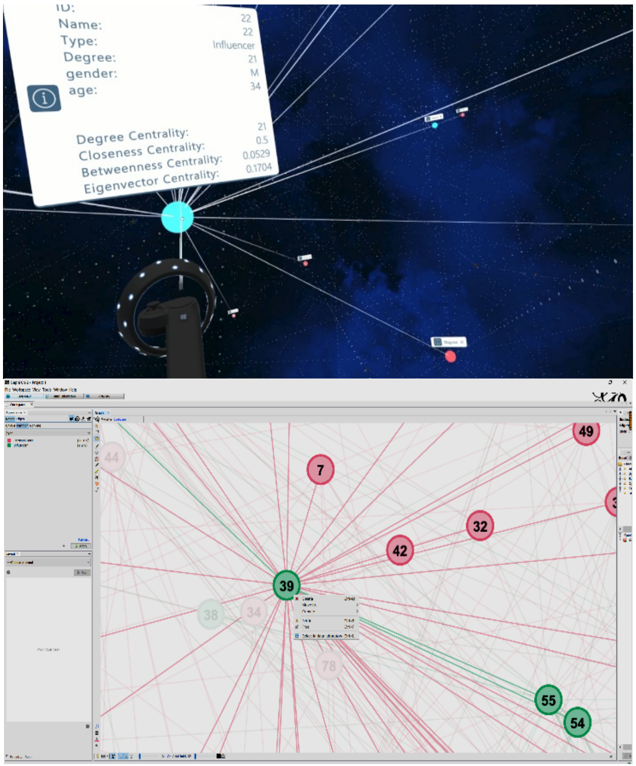

Figure 4. Aroaro displaying node properties (above) and Gephi displaying node properties (below)

3. Similar to presence under a collaborative environment, the ability to hear other decision makers' voices can correspond to either synchronous or asynchronous modes. In Aroaro, the audio tool embodies the *multi-sensory capability*. It allows users to leave recordings on designated objects in the virtual space for their collaborators to listen asynchronously.

4. The combination and utilization of the previous features facilitate a higher level of *engagement*. This is of particular importance to decision-making supported by network data visualisation.

We consider a scenario where a business organization needs to identify the most important members of the network for its commercial activities. Only information about network connectivity, that is, the bilateral relationships between nodes or members of the network, will be used. We appeal to known measures of network centrality, more specifically quantitative descriptors associated with a node, such as degree, betweenness, closeness and eigenvector. Given a node, the following descriptions of these measurements are useful:

Centrality measurement	Definition
Degree	the number of nodes that share a link with the node
Closeness	the average inverse distance of the node to all other nodes.
Betweenness	the fraction of shortest paths between any two nodes of the network that contain said node.

Closeness gives an estimate of the power of a node to spread information efficiently through the network. This is a measure of indirect influence. When a node's closeness is high, its distances to all other nodes are typically shortest. Betweenness centrality indicates the influence a node has over the flow of information in the network. This measurement is akin to estimating the amount of control a node may exert on the flow of information within the network. These measurements are pre-computed when the network data set is stored in Aroaro for the first time.

On its own, each measurement can be used to rank the nodes of a network. Factoring out the fact that ties may appear, the rank is unambiguous, and the most important node can be determined. However, considered together, even if only for two nodes, the measurements may not determine unambiguously what the most important node is. This is because not all rankings produced return the same order. Although, it is certainly observed that nodes with a low degree tend to rank low on the other measurement rankings, as we narrow down our search for highly connected nodes, we may encounter difficulties in deciding which node to choose as being the most important.

IV. EXPERIMENTAL METHODOLOGY, SOFTWARE AND HARDWARE

We now turn to the determination of the most important members of a network, given that network information is available in two distinct ways. First, each network member, represented by nodes, is classified as either "influencer" or "regular member". Second, network relationships are represented by links.

Experiments consisted of explaining the purpose of the experiment to the invited lab subject, in the first place, and then continued with a demonstration of the devices and platforms to be used in the experiment. The experiments aimed to elicit answers on three related and increasingly more complex aspects.

Both Aroaro and Gephi were fed the same network data set. Demographic information for each node was available and displayed on a label by simply activating it from the user's menu. The values of centrality measurements, discussed above for the node, could also be seen on the label. A subject could then use the information on the label to answer the questions. Subjects were informed and trained on manipulating the visualisation tools to gain a different visual perspective when they considered it necessary as, for instance, in their judgement a node's label information would not be enough for answering the question.

We compared the immersive VR environment and the 2D flat screen visualisation facility in terms of speed, effectiveness, and quality of the decisions made. Speed refers to the time a decision maker took to answer each question, finishing a task or selecting while engaging with each visualisation tool. Effectiveness refers to the subject's reaction to the environment usability and the ease with which tasks were performed. Quality of decisions can be determined based on observation and analysis of the responses to standard and more demanding questions.

To study which environment, either a VR-based environment or a 2D desktop-based visualisation facility, would allow subjects to make faster, more effective and/or higher-quality decisions, a within-subject study was conducted with 15 participants who were randomly divided into two groups.

Every participant, referred to here as "decision maker", was read a story which asked them to play the role of a mid-manager in charge of advising a marketing campaign. As repetition of the questions for a single decision maker in both environments was to be avoided, the question sets for the two platforms were phrased slightly different. Three questions were deemed Low Cognitive-Effort (LCE) questions. These questions were cognitively uncomplicated and helped us record response times both in Aroaro and Gephi for each participant and their level of understanding of the basic postulate of a centrality measurement. An LCE question did not entail a cognitive effort beyond what was already required from participants in terms of understanding how a graph is a representation of the information about connectivity contained in a network.

The other questions, deemed High Cognitive-Effort (HCE) questions, were cognitively more complex, referring to choices over the members (influencers and regular members) of the fictitious social network coded in the network data set. These questions required participants to engage in visualisation of the corresponding data set to make decisions based on multiple attributes and measurements of its component nodes.

The decision maker needed to make twelve decisions (split into two groups of six) to support the fictitious marketing campaign by using both platforms. To remit any order effect, the first group of decision makers used Aroaro first, and the other group used Gephi first. Decision makers were shown the way each tool interprets and displays a network data set, taught the meaning of degree centrality, closeness centrality and betweenness centrality, and assisted with preliminary tests to recognize nodes.

Figure 5. User controls which node's information to display by means of a menu

Figure 5 shows how a decision maker would interact with Aroaro to display information about the network nodes. An illustration of the type of situations faced by a decision maker when answering a HCE question is presented in Figure 6. The figure shows two nodes that centrality analytics found to be of high importance, with neither node raking consistently highest in all centrality measurements. The decision maker then needed to inspect attributes of the nodes' neighbors to support their final choice.

We recorded the answers and the response times to questions as they would be used as proxies to indicate the level of success in the effort spent by a decision maker. We also recorded the reasons decision makers expressed for their decision. The quality of answers to HCE was evaluated in 3 levels: low (1), acceptable (2) or outstanding (3), whereas the quality of answers to LCE questions was recorded as either right (1) or wrong (0).

Figure 6. Two nodes compete for the decision maker's attention in Aroaro

Each decision maker responded pre and post questionnaires. Pre-experiment questionnaires collected baseline information about each lab subject: age, gender, and level of education, as well as information about the subject's vision conditions and skills including prior VR/AR experience. A post-questionnaire recorded the participants' experience with Aroaro and Gephi in terms of maneuverability, task effectiveness and satisfaction.

V. RESULTS AND DISCUSSIONS

The experiment required participants to consider multiple attributes and discover hidden relationships in the data set. All participants provided answers for all six questions in Aroaro's VR immersive environment and almost all participants made decisions for all six questions using a 2D desktop platform in Gephi. Two participants failed to make a final decision for one HCE question in Gephi. Most participants responded to the LCE (easy) questions quickly with a high quality of decisions on both the immersive platform and 2D desktop platform

Figure 7 shows the average time spent by the participants on each question and platform. For the first three questions (LCE), participants spent typically more time in Aroaro. In contrast, on the next three questions (HCE) participants on Gephi took longer on average. Participants in Aroaro spent slightly more time on Q4 compared to the corresponding question, Q10, in Gephi on average. On average, they spent much less time on Q5 and Q6 in Aroaro compared to corresponding questions Q11 and Q12 in Gephi.

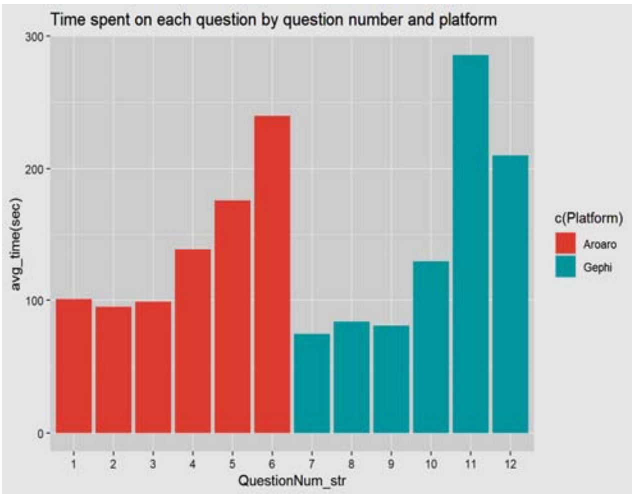

Figure 7. Average time spent on each question

As seen in Figure 8, answers to HCE questions on Aroaro displayed a higher quality index than their counterparts on Gephi. On average, the LCE responses on Aroaro had a slightly higher quality index than LCE responses on Gephi. (Remember that HCE answers were coded as low (1), acceptable (2) and outstanding (3), whereas LCE answers were coded as right (1) or wrong (0)).

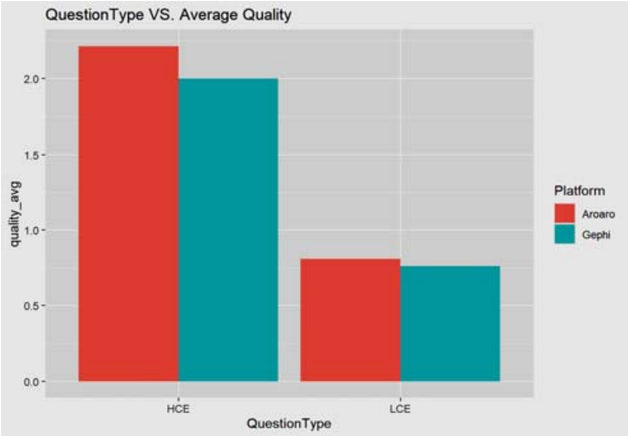

Figure 8. Average quality of answers per question type

Participants seemed to have performed better on Gephi when they worked first in Aroaro. This, however, did not seem to be the case for Aroaro. Even when Gephi was the first platform, participants in Aroaro had lower performance compared to when Aroaro was first used. This can be seen in Figure 9. For both platforms, when they were used in the second round, response quality was slightly better. However, responses in Aroaro always displayed a higher quality regardless of the order of use of the condition.

In the post-questionnaire, the immersive platform, Aroaro, was reported to be more enjoyable than the alternative by fourteen participants. Only one participant preferred the 2D desktop. All participants enjoyed making decisions in the immersive platform, but only one participant expressed an enjoyable experience on the 2D desktop platform. The questionnaire indicated that most participants felt the immersive platform is easier to use for decision-making than the 2D desktop platform.

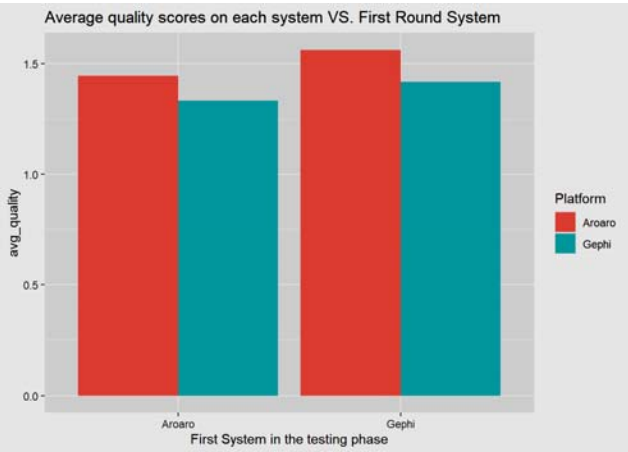

Figure 9. Average quality scores and first system used

Participants' perceptions of their experience with the two visualisation environments seem to suggest a difference between the easiness and comfort about their decisions on each platform. It seems that subjects considered immersion in Aroaro more useful. This suggests the potential for immersive virtual spaces to help decision makers overcome cognitive roadblocks in the process of discovering associations, relations and features of the data.

VI. CONCLUSIONS AND FUTURE WORK

This paper reports on the utilization of our newly created mixed- reality, multi-user software platform. It is used as an immersive environment for network data visualisation, among other data set choices, to support more effective and/ or higher-quality decision-making in the context of analysis of information contained in a network data set.

Lab experiments were designed to accommodate two visualisation platforms, one being our own immersive mixed-reality platform with a network data visualisation module, and another being a 2D flat-screen display. Lab subjects used the platforms to answer a set of questions posed within the context of a fictitious marketing campaign. Our goal was to compare the utilization of the two platforms.

The results obtained thus far are only preliminary. We believe they are robust enough to point in the right direction and can be used in hypothesis formulation, but not statistically significant to draw definitive conclusions.

In terms of responsiveness, participants spent less time making decisions posed through HCE questions in Aroaro than the alternative. Further, the quality of decisions, measured by scores on the answers provided, was higher when the participants experienced Aroaro's VR environment than their using the alternative. This result is less obvious for LCE questions and more appreciable for HCE questions. Participants seemed to have performed better on Gephi when they worked first in Aroaro. However, when Gephi was the first platform used, participants in Aroaro had lower performance compared to when Aroaro was first used.

It is encouraging to observe most users considered our platform easier to use than the alternative. Also, as users explored the virtual environment and felt comfortable discovering its features, they became more curious about the object of visualisation. The latter suggests what is reported in earlier immersive analytics experiments that the richness of the environment invites exploration.

Besides, making our study statistically ore robust, we will extend our work to multi-user, team decision-making to addressing some unresolved challenges on collaborative visualisation [9].

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