OA-GRAPHS: ORIENTATION AGNOSTIC GRAPHS FOR IMPROVING THE LEGIBILITY OF SIMPLE VISUALIZATIONS ON HORIZONTAL DISPLAYS

by

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ABSTRACT

Horizontal displays, such as tabletop systems, are emerging as the de facto platform for engaging participants in collaborative tasks. Despite significant efforts in improving the interactivity of information on such systems, very little research has been invested in understanding how groups of people view data visualizations in such environments. Numerous studies introduced different techniques to support viewing visualization for groups of people, such as duplicating or reorienting the visual displays. However, when visualizations compete for pixels on the display, prior solutions do not work effectively.

In this thesis, I explore whether orientation on horizontal displays impacts the legibility of simple visualizations such as graphs. I have found that users are best at reading a graph when it is right side up, and takes them 20% less time than when it is read upside down. The main objective of this thesis was to investigate whether the readability and understandability of simple graphs can be improved. I have introduced the Orientation Agnostic Graph (OA-Graph) which is legible regardless of orientation. The OA-Graph uses a radial layout which has several interesting properties such as implicit orientation, points equidistant to center, and flexible rearrangement. OA-Graphs perform better than graphs that are presented upside down. I have converted several popular types of graphs into their OA counterpart for improved legibility on tabletop systems. Guidelines are presented that describe how other visualizations can be converted to being orientation agnostic.

PUBLICATIONS

Some ideas and figures in this thesis have appeared previously in the following publications:

Fouad Shoie Alallah, Pourang Irani, and Dean Jin. OA-Graphs: Orientation Agnostic Graphs for Improving the Legibility of Charts on Horizontal Displays. In *ITS '10: Proceedings of the ACM International Conference on Interactive Tabletop Surfaces*. ACM, Saarbrücken, Germany, November 2010. ACM Press.

Fouad Shoie Alallah, Pourang Irani, and Dean Jin. MeetViz: A Tool for Visualizing the Social Interactions in a Face-to-Face Meeting, In *IV '08: Proceedings of the 12th International Conference Information Visualization Poster Session*, Columbus, Ohio, USA, 2008.

Fouad Shoie Alallah, Mahtab Nezhadasl, Pourang Irani, and Dean Jin. Visualizing the Decision-Making Process in a Face-to-Face Meeting. In *IV '07: Proceedings of the 11th International Conference on Information Visualization*. pages 168-176, Washington, DC, 2007. IEEE Computer Society.

Obstacles are those frightful things you see
when you take your eyes off your goal.
— Henry Ford

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ACRONYMS

API Application programming interface

ANOVA Analysis of variance

HCI Human-Computer interaction

FTIR Frustrated total internal reflection

GUI Graphical user interface

OA-Graph Orientation agnostic graph

PyMT Python multi-touch applications

UI User interface

1

INTRODUCTION

Tabletop displays effectively combine computational resources with traditional physical desk spaces to provide a powerful platform for supporting collaborative activities. Researchers have developed different techniques, interfaces, and visualizations to tackle the issue of viewing data visualizations during collaborative tasks in tabletop displays. When people gather around a table, their collaboration involves different activities. An example of such activity is sharing information placed on the tabletop surface including objects, documents, pictures, and charts. In face-to-face settings, the cooperative work on tabletop surfaces leads to noticeable issues such as orientation and view perspective. When a user interacts individually with a tabletop, orientation may not be a crucial problem since objects can be displayed and adjusted toward him or her. On the other hand, for groups of users gathered around a tabletop, sharing a common perspective of the displayed information is difficult. This becomes a crucial issue for groups of people because their perspective is strongly correlated with their location around the tabletop. Each user in the group will perceive the information in a different way since they are viewing the information from different locations. Figure 1 shows an example of two users viewing a graph.

I reviewed and identified a number of limitations with existing techniques and their visualizations that address the orientation of information. I then investigated the orientation effects of particular objects such as graphs in a tabletop setting. I examined charts that have been used widely in many common applications that would typically benefit from collaborative input. The Orientation Agnostic Graph

(OA-Graph) is presented as a mean for coding data for tabletops as an alternative presentation for charts. This alternative representation improves the legibility of charts across different orientations. This should have the net effect of improving the collaboration process around a tabletop.

The remainder of this thesis is structured as follows: In Chapter 2, I discuss how researchers have addressed orientation issues generally and categorize different techniques and solutions. Chapter 3 provides a description of the characteristics of chart visualization in horizontal displays. In Chapter 4, a detailed discussion of orientation effects of charts in a tabletop setting, design criteria and process of the OA-Graph, and the evaluation of OA-Graphs are presented. In Chapter 5, I discuss the specification and implementation of the OA-Graph interface. In Chapter 6, I apply the OA-Graph concept in common chart visualizations. Finally, the document ends with a summary and suggestions for future work.

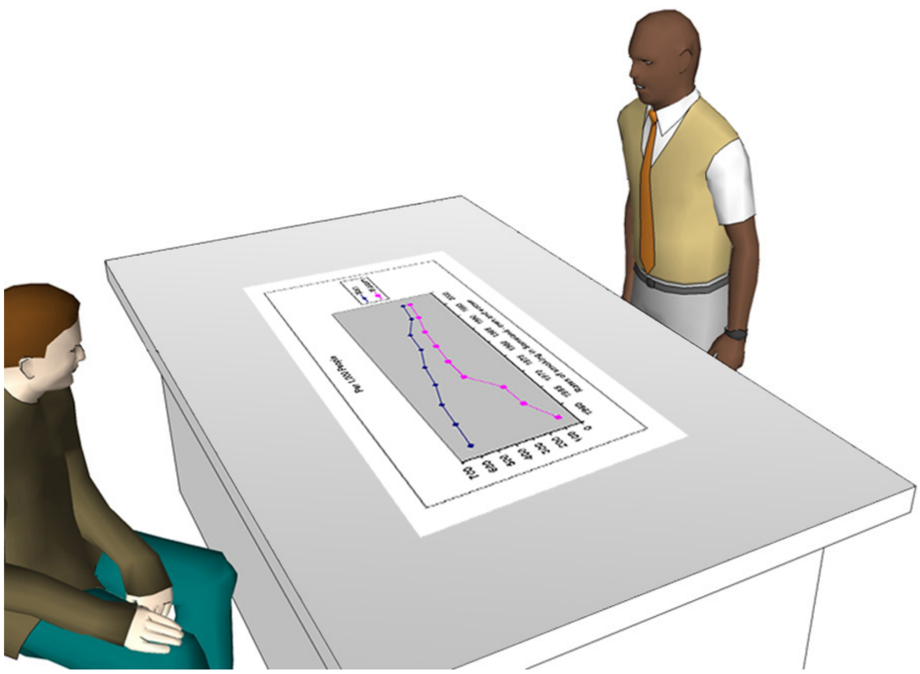

Figure 1: The user on the right views the graph in the right direction. The user on the left side of the tabletop views the chart upside down.

2 RELATED LITERATURE

This chapter briefly introduces tabletop displays and their potential. Work devoted to the study of human perception and performance of object orientation as well as different interaction techniques in the first set of related work are reviewed. Following this, a survey of the different visual encoding systems that have been used to represent information is presented.

2.1 POTENTIAL OF TABLETOP DISPLAYS

Tabletop displays take advantage of flat surfaces such as a table or desk to provide an effective platform for collaboration [20]. A physical table is commonly found in homes, workplaces, or public spaces. Collaboration activities usually involve people making use of synchronous and asynchronous communications. A number of interactions can occur during a collaboration session including drawing, calculating, sharing, spreading out, and organizing objects. With the improvement of computational technology, such activities can now be applied to digital information. The vision of coupling physical objects on flat surfaces with digital information is a reality. This was the motivation behind the first generation of flat displays. DigitalDesk [60] and ClearBoard [26] were the pioneers of tabletop displays. DigitalDesk was introduced by Wellner [60] and was aimed at coupling the use of paper and digital documents on a desk surface. The DigitalDesk system used a camera and a projector located above the work desk. The camera detected where the user was pointing at the surface and also recognized the content of paper documents placed on it. The result was a table with the characteristics of a personal computer. On desktop computers, users infrequently carried out collaboration tasks that required working with each other and sharing objects. Ishii et al. [26] introduced the ClearBoard system. It was directed more toward exploring the potential of supporting collaboration of multiple users sitting face-to-face. Ishii et al. looked in detail at different patterns that occurred during a teaching session. They analyzed a collaborative tutoring scenario where a teacher instructs a student on how to play the game backgammon. The study showed that there are noticeable gaze patterns for each user. The student spent more time looking at the game board while the tutor was getting feedback about student performance by looking at the students' moves in the game board and their facial expressions.

Horizontal displays are the next logical step toward the creation of an environment that effectively combines computational resources with traditional physical desk spaces to provide a powerful platform for supporting collaborative activities. It is an ideal solution for a traditional computer since it supports group collaboration, interaction and information sharing among multiple users. For instance, traditional computers such as desktops, laptops, or handheld devices have difficulties in viewing the screen from different angles for a group of people. Also, it is not easy for a group to collaborate using single input/output devices such as a mouse, keyboard, and monitor. Researchers have looked at different designs for tabletops that serve different purposes (such as collaboration) and explored issues (such as orientation of shared information) associated with them.

2.2 ORIENTATION ON TABLETOP DISPLAYS

Since tabletops have different physical structures than the traditional computer (i.e. vertical displays), they create unique challenges for their users. To illustrate, on vertical displays, all users have the same upright view to some degree. In a traditional tabletop, people view the material on the surface from different perspectives unless they are closely positioned side-by-side. The view of the users is correlated with their location around the display. In a face-to-face setting, collaboration involves sharing information placed on the tabletop display surface including objects, documents, pictures, and charts. For a single user at a tabletop, display orientation may not be a crucial problem. Objects can be displayed and adjusted toward the user. However, for groups of users gathered around a tabletop display, object orientation becomes critical. In such a setting, users do not share a common perspective of the displayed information. Orientation may have less of an effect on users if the information viewed on the tabletop display is orientation-independent such as a model and shape. However, several types of shared information are orientation-dependent such as text, pictures and graphs. When users view the information from different viewpoints, the information may be perceived differently since the users' perspective is strongly correlated with their location around the tabletop. For example, consider a scenario where a group of people are involved in collaboration around a tabletop display viewing graphs. A chart will appear right side up to one participant and upside down or sideways to other participants. Since each participant has a different perspective, it can cause them to misunderstand or misinterpret the presented information. Ultimately, the information comparability of each participant will be affected during the collaboration process (see Figure 1).

2.2.1 *Text and object orientation on non-computer based system*

Several decades ago, researchers looked at the process of shape and text reading recognition at different orientations, transformations, and positions. To understand oriented object recognition in humans I present a brief overview of perceptual studies on how the human brain processes and recognizes disoriented objects. A number of studies have looked at the human ability to manipulate spatial orientation. This is referred to as *mental rotation* [46]. In the psychology literature, Shepard and Metzler [46] conducted a series of studies to explore the mental rotation phenomenon. In their experiments, subjects were required to make a comparison of a pair of perspective line drawings in different orientations as fast and as accurately as possible. Subjects have to verify whether the two portrayed objects are identical or not. An example is shown in Figure 2. The object is a combination of solid cubes attached to each other forming arm-like shapes. It is worth mentioning that in their experiments they used two types of rotation: simple (one degree of freedom rotation) and complex (two degrees of freedom rotation). The research concluded that mental rotation reaction time for both types of orientation is positively correlated with the degree of object orientation.

(a) Identical portrayed objects with different orientation of 80° (simple orientation).

(b) Identical portrayed objects with different orientations of 80° in depth (complex orientation).

(c) Different objects, which cannot be brought into congruence by any rotation.

Figure 2: Examples of pairs of object drawings shown to subjects in Shepard and Metzler experiments [46].

Cooper [12] examined the relationship between mental rotation and the complexity of shape representation to determine if it has a similar effect on reaction times found by Shepard and Metzler [46]. In his experiment, subjects were presented with eight random irregular forms. An example of the irregular forms is shown in Figure 3. After subjects practiced trials with different types of irregular forms, they are then asked to press, as fast as possible, the right-hand button for standard or the left-hand button for reflected based on their belief about the correct answer. The shapes were oriented clockwise at 60°, 120°, 180°, 240°, and 300° from the trained orientation. One of the main findings of the study is that participants were faster in identifying the standard shape than the reflected shape.

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Figure 3: The eight different irregular shapes, the number of points in each shape represent the level of complexity in the shape. Subjects need to identify standard versions of the form from their reflected counterpart [12].

Researchers have done several experiments in an attempt to understand the orientation effects on reading text. Cooper and Shepard [13] used an approach similar to Shepard and Metzler [46] to examine the effect of orientation on single characters or numbers. In their study, individual characters were rotated (angle variation of 60°) and/or mirror-reversed letters or numbers. Participants were then asked to identify whether the letter is upright or mirror-reversed. Not surprisingly, their findings were similar to Shepard and Metzler [46]; the reaction time of subjects increased with orientation angle. Another study of text reading was carried out by Huey [23]. He concentrated on comparing the reading speed in vertically and horizontally aligned text, and recognition of words based on portions of words (suffix and prefix) in an attempt to observe eye movements while reading. Kolers and Perkins [28] examined the user performance of recognizing a single character. Their studies showed that user performance when naming single inverted characters was slower than when the character was upright by an average of 44% [28]. Additional studies have found that there was no significant time difference in recognizing whether a letter belonged to a set of six letters or not [14] or between recognizing one-digit and two-digit numbers [56].

A further investigation combining several characters was performed by Kolers and Perkins [28]. They found that the speed of reading random grouped and ungrouped characters has no significant difference when presented upright. However, when the random grouped and ungrouped characters were inverted, users were slower reading on average of 30%.

Also, they found that users are better at recognizing individual letters than 'Pseudowords' with varied letter frequency and word lengths [28]. Tinker [57] was one of the first to investigate in depth the effect of text orientation on the reading process. He examined the readability of text at different orientations based on the *Chapman Cook Speed of Reading Test* found in Chapman [9]. In the experiment, subjects had to read as fast as possible through a passage and spot (by crossing at or speaking out) words in the passage that did not fit in the sentence. The analysis of the experiment data showed that text readability dramatically decreased with the increased angle. To illustrate, users performed 52% slower when the orientation of text was at a 45° or -45° angle. When users read text at a 90° or -90° angle, they performed four times slower than reading text in a normal direction. Also, Tinker conducted another experiment to examine user performance using the *Luckiesh-Moss Visibility Meter* (Luckiesh [35]) on oriented text. The *Luckiesh-Moss Visibility Meter* is a photometer that consists of two variable-density filters. Each filter is assigned for each eye that is adjusted which allows object to be seen barely discernible through them. The Luckiesh-Moss Visibility Meter emphasizes different factors of hygenic conditions for seeing such as size, contrast, brightness, and time, which determine the visibility of an object. The study concluded that not only visibility factors have an effect on the readability of the text but also text orientation was a major factor on reading speed.

Another study was conducted by Koriat and Norman [29]. They examined user awareness of text (word or non-word) in orientations, with increments of 20° at a time, and their ability to recognize this text[1]. Their study showed that there is no significant difference in user performance when the orientation ranges from 0° to 60° clockwise and counterclockwise. In that orientation range, there is no effect of word length or orientation on word recognition. However, when the text orientation is between 60° and 120°, there was a significant effect of text length and orientation which yielded slower users response times. Above 120° in either direction, the word identification times increase by up to 80%. In addition, for orientations over 120°, the time to recognize words varies based on the number of letters in the word. For example, for two and five letters words, the reduction of reading speed were 50% and 220% respectively.

Tabletops are one application domain that can benefit from this research since perspectives of a tabletop display change for users based on their position around it. However, Tinker's [57] and Koriat and Norman's [29] studies were limited to the head and body movements of participants which raises the question of their relevance to tabletop applications [61].

1 The subjects were native Hebrew speakers; they performed the experiment on Hebrew letters.

2.2.2 *Orientation on tabletops and collaborative actions*

A large amount of research has focused on tabletop displays to support collaborative groupware as the main objective [1, 40, 53]. Researchers have built on previous work related to orientation issues and applied it to collaborative tabletops [30, 31, 55, 61]. These studies have looked in detail into the applicability of tabletop displays as well as collaborative groupware. Wigdor and Balakrishnan [61] conducted two experiments each with two objectives: (1) measure the effect of orientation on readability at various locations (top-left, top-right, bottom-left, and bottom-right) and orientations on the tabletop; and (2) measure the effect of orientation on readability at various locations and orientations for users performing collaborative tasks. Subjects were asked to read, memorize, and type the presented stimuli. The system captured the time from when stimuli appeared up to when the user started to type in the stimuli. The stimuli were a single word, a short phrase, and a 6-digit number, oriented at every 45° of rotation. The head and body movement of the subject were not constrained which differs from the Tinker and Koriat and Norman studies. The experiment result showed a similar orientation effect of the text readability speed to the previous experiments. However, it was less dramatic than what Tinker and Koriat and Norman found. The analysis of the data showed that there are effects for rotation between 45° and -45°. Nevertheless, the performance rapidly increased beyond that, from 25.7% to 64.7% in reading speed. Also, they found that in the single word and short phrase condition at orientation angles of -135° and 135° performance did not significantly differ in recognition time. On the other hand, there were significant differences in the recognition time at orientation angles of -90° and 90°. For the 6-digit number condition, the reading speed performance suffered the most from the orientation effects.

Wigdor and Balakrishnan [61] found a similar pattern to that found by Koriat and Norman [29]. The reading speed of subjects, for both words and phrases, was slowest for both upper locations at -135° and 135°. Wigdor and Balakrishnan thought that orientation would have a different effect among a group of subjects conducting collaborative tasks. In a second experiment, a list of 24 words with 5-6 letters each was placed in random locations oriented at various angles ranging from 0°, -45° to 45° and -135° to 135°. Each word had a suffix, and a colon followed by a number (ex. book: 3). The users' tasks were to screen elements and identify the desired element. Then they typed in the corresponding number beside the word using the keyboard. Although the average search time was insignificant, the search time for all orientations greater than 0° was 18% more.

Orientation of information can be used to enhance coordination and communication among users despite the fact that coordination and communication are considered to be human factor issues. Observational studies of physical collaboration that occur during face-to-face collaboration can be found in [54, 55, 31]. The orientation interface of objects on a tabletop could facilitate interaction among users. Tang [54], Kruger et al. [31], and Fitzmaurice et al. [17] have noticed situations where users employed orientation to serve different purposes. In some scenarios, users do not use an upright orientation. Orientation supports different objectives that assist in the collaboration process such as establishing the intended group members, creating personal or public workspace, and determining the ownership of artifacts in the tabletop [54, 31, 24, 26, 30]. Kruger et al. [31] conducted a study to compare and analyze users collaborating on puzzle solving tasks, in physical (versus electronic) tables and on vertical (versus horizontal) displays. In an attempt to explain the role of orientation in the collaboration process, they focused on certain questions about rotation on tabletop displays in the context of puzzle solving:

Q1- What are the users' objectives for reorienting objects and how did they achieve it?

Q2- Are there orientation effects on subsequent user behavior?

Q3- Are there verbal and/or physical behaviors associated with the use of orientation on a tabletop?

Q4- What are the different interactions performed by users during the collaboration process?

In regard to the first question, they identified different behavioral instances of orientation usage. Subjects used rotation 32.7% of the time for themselves, 34.7% of the time for others, and 32.7% of the time for themselves and for each other. Another observation is that orientation was used differently in different display territories. Subjects used rotation 23.5% of the time within their own personal territory whereas 35.7% of orientation was used within the group territory. Also, there were different uses of orientation in the puzzle assembling area and when previewing images. Since group members collaborate mainly in the puzzle assembling area (referred to as primary group orientation), subjects used an orientation 66.3% of the time. Participants used rotation of objects in the image preview area 25.5% of the time. Kruger et al. [31] found an effect of orientation on the subsequent behavior of users. During the process of solving the puzzle, subjects picked up and rotated pieces of the puzzle toward themselves 33.6% of the time, and 13.8% of the time picked up and rotated pieces of the puzzle toward others. Interestingly, when a group collaborated in solving part of the puzzle, 52.6% of them picked up the object at a compromised angle. This shows that subjects are more likely to work with objects that are oriented toward them when the subjects engaged in collaboration tasks. Verbal comments and physical gestures were seldom used by subjects with any action that required rotation of objects. Direct comments and gestures that involved orientation action were only used 15.3% of the time. The only comments that were observed involved establishing group orientation and feedback about orientation of the collaborator's gesture.

In regard to gestures, two gestures related to object rotation were observed in the study. The interaction of subjects with puzzle objects showed that they used more orthogonal rotations (56.1%) than non-orthogonal rotations (43.9%). In addition, similar patterns have been identified for orienting puzzle pieces on a table or while pieces were being held in a person's hands. Subjects used orientation on a table 55.1% of the time and in their hand 44.9% of the time.

2.2.3 *Techniques for orientation manipulation on tabletops*

Several techniques have been developed for dealing with orientation by either assisting tabletop users in manipulating the orientation of objects, removing the problems, or by providing orientation control [42, 21, 44, 45, 32, 38]. Several design guidelines for co-located tabletop collaboration have been highlighted by Scott et al. [42]. One of these guidelines is to grant horizontal display users shared access to physical and digital objects. Tabletop interfaces have to support different kinds of activities with flexible user interaction from a variety of positions around the table. Manual and/or automated object rotations are used as common practices to reduce the effect of orientation [21]. A range of interaction techniques have been developed to assist in manipulating the orientation of objects in order to achieve effective collaboration in these environments [42]. These techniques use several approaches to address orientation issues [31]. Kruger et al. [31] categorized these approaches into *fixed orientation*, *manual orientation*, *multiple copies*, *person-based automatic orientation*, and *environment-based automatic orientation*.

Fixed orientation:

In the fixed orientation approach, objects are oriented in one direction only due to the assumption that users will be seated shoulder-to-shoulder with other participants. This approach can be found in DiamondSpin [44]. The DiamondSpin Java toolkit is built on a polar coordinate system that transforms Cartesian coordinates into polar coordinates using a multi-threaded application. As a result, multi-views are supported in real-time, providing users with an ability to orient each artifact individually. In addition, users can rotate the entire tabletop interface. Several applications have been built on the DiamondSpin engine such as *UbiTable* [43], *Table for N* [44], *An Opportunistic Browsing Coffee Table* [8], and *A Tabletop Collage and Webpage Builder* [44]. Another example that used the same approach is Attribute Gates [52]. Attribute Gates is a user interface that includes orientation among the object attributes of documents. The interface supports moving documents between user territories on flat surfaces. The control is placed in the center of the tabletop so that users can change the document properties while they are passing it to other users. The control has a set of properties where users can choose desired attributes (see Figure 4).

Manual orientation:

Manual orientation is one of the simplest ways to handle the orientation of information in tabletops since it, to some extent, simulates the way individuals interact with physical and media artifacts such as papers, pictures, and graphs. Each group member around the tabletop has an ability to orient digital objects. A number of systems have considered including manual orientation interaction in interface techniques. *InteracTable* [49, 50] is able to detect the location of users around the table. The system has several interaction modes. One of these modes gives users the ability to make round movements using pen-based input to orient the displayed object. *DiamondSpin API* uses a similar approach. *DSContainer* has the functionality for handling the manual orientation of interfaces for documents.

It also allows users to manually orient the entry system interface [44]. Hancock et al. [21] introduced combined manual rotation and translation of documents using two-finger touch to allow smooth and comprehensive movement [21].

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Figure 4: The Attribute Gates interface allow the user to drag documents over various controls to change the document properties. In this figure the user crosses three controls (read and write, rotate, and decrease size) before passing it to the other user [52].

Replicated copy:

One approach to address the orientation issues in collaborative environments is to use multiple copies of objects, providing multiple controls for orienting. By doing so, each user has their own copy of the same objects oriented toward them. This approach has been widely used by tabletop researchers [50, 38].

Streitz et al. [50] have used the same approach in the *BEACH Architecture* and more specifically *InteracTable*. Users can manipulate information objects on the tabletop by displaying, discussing, and annotating them independently. Any manipulation of an object is reflected on other copies of the same object. Object manipulation is done using pen or finger gestures. Shared objects can be duplicated and positioned individually by users in different locations. *InteracTable* consists of four areas: top, bottom, left, and right. Individuals can shuffle single or groups of objects, orienting and arranging them dynamically.

Morris et al. [38] introduced the TeamTag system for collective annotation of objects in co-located tabletop groupware settings. The system interfaces have centralized and replicated layouts for control widgets (i.e., menus). An example can be seen in Figure 5. In the centralized layout, users basically share controls with each other. These controls are circles that are subdivided into sectors. Each of the circles presents metadata related to the pictures and each sector has a value that corresponds to a specific metadata presented. The controls are located and locked in the center of the display. Users can rotate the control to get better views of the items. Once the user removes his or her hand, the control gets an initial orientation.

Users can relocate pictures around the edge of the table. The picture dynamically adjusts its orientation toward the user who is at the closest side of the table. Users can use a finger to select a picture and then tag it with associated metadata. The replicated controls consist of stacked rectangles, and contents are oriented toward users at each edge. Photos are arranged and located in the center of the display. Individuals use these controls to interact with group of photos at the center of the display. An evaluation study using TeamTag has shown that subjects have a strong preference for replicated controls over centralized controls. It provides a central area for collaborative work and avoids accidental touching of collaborators' hands.

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(a) In the replicated layout each user has the same controls and the documents appear in the center of the interface.

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(b) The centralized layout arranges the controls in the center of the interface and the documents are laid out on the edge of the table. The shape of the controls is radial and the labeling arrangements circular.

Figure 5: The TeamTag system for co-located tabletop groupware setting [38].

Person-based automatic orientation:

Person-based automatic orientation is another approach that is meant to overcome manual orientation. The idea behind this approach is that artifacts are oriented toward the individual who has most recently accessed the artifact. Tandler et al. [53] have introduced a system that dynamically extends the size of an interaction display. Two *ConnectTable* interaction displays can be coupled into one interaction platform. Each user can work on their own personal spaces. When there is need for collaborative work, users attach both displays head to head which also creates face-to-face communication between both users. Once both displays get close to each other, a homogeneous display area is created, (see Figure 6). Individuals can interact and exchange information in compound interaction areas by shuffling objects from one display to the other using pen-based inputs (Figure 6). When an object reaches the edge, a copy of the shuffled object is created for other users with the object rotated toward them.

Another example of this approach is found in *Rotate' N Translate* (RNT) [32]. Kruger et al. introduced a technique that combines rotation and translation to provide fluid access for users around a table using a single touch-point mouse. The RNT algorithm considers three important points: the center of the object, the location of the mouse touch, and the targeted location. These points determine the technique behavior. The orientation and translation of the document can be achieved by clicking any corner and moving it to the desired location. The center of the document at the targeted location becomes the new position (Figure 7).

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(a) When two users want to collaborate, they place each ConnecTable head to head which enables a homogeneous display area.

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(b) Once the homogeneous display area has been created, individuals can exchange artifacts.

Figure 6: The homogeneous display area of two ConnecTables (Figure a). When a user passes a shared artifact to the other (Figure b), each user ends up with a copy of the artifact rotated toward them [53].

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Figure 7: The left side of the figure shows the movement that causes translation. To rotate and translate the document, user has to touch out side the virtual circle boundary as shown on the right side of the figure [32].

Environment-based automatic orientation:

Different automatic orientation frameworks have been introduced to solve the orientation issue. The idea behind these approaches is that the locations of users are known or detected [15, 39, 44, 59]. Nacenta et al. [39] introduced E-conic. This system collects the location of multiple users and correctly orientates a window (i.e. Internet Browser) in multiple displays dynamically so that the windows are presented towards them. The system is designed to address perspective-awareness in multiple displays. Users wear head trackers that monitor head location and movement. This collected information is used to adjust the window and cursor size and relative pixel resolution for its users. The perspective window provides users around the display with optimal visibility regardless of their position and viewpoints. The system renders the windows into a two-dimensional plane and displays it perpendicular to the user who views the window based on the location of the user or the display. Each window has several controls at the top and anchors at the top left to manipulate size, perspective, privacy, and orientation (see Figure 8). The anchor is used to attach and detach the window in different locations. The shape and orientation of the window adapt to the display and/or user movements and locations. The user wheel is divided into four colored sectors where each represents a user in the system. The colors are used to assign windows to each user in order to maintain the ownership of windows. The windows are displayed in flat mode when all users, standing at opposite sides of a tabletop, want to have the same access to the data.

Figure 8: Different controls in perspective windows. An anchor located in the top left corner of the window is used to attach it to a pixel in a display [39].

MERL's tabletop system [59, 44] is a circular tabletop interface. It supports the automatic orientation of documents based on users' locations around the display. In this system the objects are aligned radially based on their location in the tabletop. For example, when the object is at the outer edge of the tabletop, the object is automatically directed towards the user.

Dragicevic and Shi [15] have addressed some of the limitations in the rotatable circular tabletop in MERL's tabletop [59, 44]. In the circular tabletop, the system allows the user to manipulate only the location of the document. The orientation of the document is adjusted automatically to face away from the center of the table to the edge of the user location [15]. This approach may be suitable for circular tabletops, but not for rectangular tabletops. Dragicevic and Shi [15] introduced a conceptual framework for automatic orientation using a mapping mechanism that maps the location of documents into two-dimensional vectors. This framework uses a 2-D vector field to map the location of objects on the surface. The framework handles three elements dealing with orientation: generating the workspace field, visualizing the user working area, and allowing users to manipulate the workspace based on their need. When the orientation field is generated, users can use a low-pass filter technique to change orientation and movement of objects from discontinuous orientation to diagonal orientation. The framework uses visual representation of the orientation field which provides feedback for users to raise the awareness of distinct orientation areas. Two visualizations have been used: Vector-Grid or Direction-To-Hue. Vector-Grid involves drawing orientation into a gridded vector on the surface. Direction-To-Hue involves mapping the orientation into colors (see Figure 9 (a) and (b)). Users have the ability to adjust the orientation of both workspace and regions by manipulating the centripetal orientation area of workspace and regions (see Figure 9 (c) and (d)).

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(a) Vector-grid helps users notice the orientation directions using small lines.

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(b) Direction-to-hue serves two purposes: (1) to show the orientation of documents and (2) to identify users' territories.

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(c) Users can adjust the field of orientation of the entire workspace.

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(d) Each user has the ability to adjust his or her personal workspace.

Figure 9: Conceptual manipulation and automatic document orientation using vector fields [15].

2.2.4 *Visualization interfaces in tabletops*

Several visualization interfaces in different domains have been introduced to benefit from the collaboration aspect of tabletops. Karahalios and Bergstrom [27] introduced a technique that visualizes the audio conversation of a group around a table. This visualization technique has two visualization interfaces: Conversation Clock and Conversation Votes. The Conversation Clock interface captures the conversation of a group of up to four individuals sitting around a table. Individuals are represented as rectangles with distinct colors. The rectangle length represents the amplitude of the users' volume. Over an interval of time, the interface visualizes the conversation as a clockwise stream of rectangles to complete a circle each minute. After an interval time of a minute, the complete circle shrinks into the center of the interface. The second interface, Conversation Votes [6], uses the same colored rectangles to represent individual conversations, except the rectangle is not filled in. The interface represents rectangles in linear streams.

Similar visualizations have been introduced by Sturm et al. [51]. They created a prototype system that provides a real-time visual representation of the social behaviors of a small group in a meeting at the center of a tabletop. This feedback includes the speaking time of individuals, speaking duration, visual cues of the speaker's attention to the audience, and visual cues of the audience attention to the speaker. The system projects three vertically lined circles for each participant to indicate his/her social activities. When a meeting begins, the system records the speaking time of each individual and visualizes it as a light blue circle, where the size of the circle reflects the speaking duration. An orange circle represents the amount of attention each listener got from the speaker since the beginning of the meeting. The last circle is a green circle, the size of which indicates the amount of attention the speaker has received from the audience. The authors ran experiments to evaluate the system. They found that the system provided participants with feedback during the meeting that helped to influence the social behavior of participants to be more active as well as less dominant.

Other examples of visualization techniques that support different collaboration styles can be found in A System for Co-located Collaboration Work [25] and *Lark* [58]. Theses two systems provide coordinated multiple views of shared data.

Isenberg and Carpendale [25] introduced an interface that visualizes a hierarchical data and provides different representations of the data to support data comparison tasks. The system has two types of visualizations: the cladogram and radial tree layout. Figure 10 shows representations of these two types of graphs; both types are representing the same dataset. The visualizations are displayed in a panel that has a few controls that help the user to resize, move, and orient the view. The label layouts in the charts use arc-like shapes to support orientation-independence when users read the labels.

Tobiasz et al. [58] introduced *Lark* to support different presentations of tree-graph layouts. *Lark* uses the same visualization graphs as in Isenberg and Carpendale with different interaction techniques. The *Lark* interface uses view data-set, meta-visualization, and several view-panes. These three elements are connected by a visual pipeline. The meta-visualizations are used to interact with a data-set. A user touches on a data-set icon and drags it away resulting in the display of a pipeline with three interaction icons. When a user touches the desired button, the view pan displays the graph representing the data. Users can choose different tree-graph layouts from different options such as icicle, sunburst, radial cladogram, and cladogram (as shown in Figure 11).

For most visualization interfaces on tabletops, the effectiveness of the visualization, especially on the users' perceptions, has not been addressed. An evaluation of visualization elements and designs that have an impact on the effectiveness of visualization with consideration of the orientation of the visualization is needed.

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(a) Cladogram graph.

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(b) Radial tree.

Figure 10: Two types of graphs used to visualize hierarchical data [25].

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(a) Icicle plots of the data-set.

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(b) The presentation of the same data-set using Sunburst layout.

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(c) The radial cladogram uses a radial presentation of the tree graph.

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(d) The cladogram graph presents the tree graph in a hierarcical layout.

Figure 11: Different representations of tree graphs for the same information [58].

2.2.5 *Visual encoding system*

Information visualization can help users understand and gain insight from data. The representation of information is another factor that plays an important role in the perception and, more specifically, legibility of visual representations. A few pioneering studies such as Bertin [7], Cleveland and McGill [10], and Mackinlay [36], have proposed a set of basic elements to represent data. Bertin defined a matrix for encoding mechanisms that are used to provide visual representations of data and their suitability for supporting common tasks such as association, selection, order, and quantity [7]. His matrix consists of *Size*, *Position*, *Texture*, *Colour*, *Orientation*, and *Shape*. Figure 12 shows the list of visual marks and their effectiveness.

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Figure 12: Bertin's ranking of different visual variables for different tasks [7].

Cleveland and McGill [10] introduced a wider range of visual variables, called elementary perceptual tasks, that deal with the representation of quantitative data on common graphs. They ranked these visual perceptual tasks based on empirical examination into *Position*, *Length*, *Angle and Slope*, *Area*, *Volume*, and *Colour and Density*. Figure 13 shows the rank of their visual encoding matrix.

One of the main drawbacks of Cleveland and McGill's approach is that it only considers quantitative data. An extension to their approach has been introduced by Mackinlay [36]. He looked at quantitative and non-quantitative data, examining visual encoding systems for different data types. He categorized the efficacy of visual variables based on characteristics of three data types: ordinal, nominal, and quantitative (see Figure 14).

The majority of existing charts use one of the aforementioned encoding systems. However, when viewed on a tabletop, most charts are unidirectional, meaning that only one person will see the object in the right view. More attention to the applicability of using the same representation for data on a traditional desktop to a tabletop is required. Designers need to consider the challenges involved in working collaboratively in tabletop environments when developing interfaces and displays for charts. The interfaces provided and the representation of data has to be appropriate and should consider scenarios for single-user or multiple-user views. A number of prior studies have examined visual encoding variables and their effect on the comprehension of data sets [25, 58]. A question arises about the validity of a data encoding system designed to represent information on traditional desktops when applied to a tabletop setting. Interface designers have to consider the different perspectives of tabletop users. Information such as charts shown in tabletop groupware use an encoding system that assumes the data will be oriented toward the user with an orthogonal line of sight. Wigdor et al. [62] examined the perception of a subset of the basic graphical elements proposed by Cleveland and McGill. They found that distortion has less impact on some graphical elements than others. Wigdor et al. used a similar experimental task to Cleveland and McGill with some modifications to it.

Participants were asked to compare the magnitude of one object to that of three similar objects. The first object, or modulus, and the three other objects, or stimuli, were placed at different distances in vertical alignment and in vertical and/or horizontal displays. Magnitude was expressed as a percentage. For visual elements in a tabletop setting, they found the following:

1. The accuracy of visual elements increases if the vertical distance between them is 0 cm at any position of the tabletop.

2. The greater the distance between visual elements, the less accurate the relative value perception will be.

3. The accuracy of certain visual elements is higher than others, in horizontal and vertical orientations. The order of elements from most to least accurate is: length (horizontal), length (vertical), position (horizontal), angle (horizontal), area, position (vertical), angle (vertical), and slope.

4. Slope is the only visual element that has a high error rate when the modulus and stimulus distance are far apart on the right and left sides of the tabletop.

Using these design recommendations for more complex visual presentations (such as charts) may reduce the effects of distortion. Empirical evidence is needed to support this assumption.

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Figure 13: Cleveland and McGill's encoding system [10] which is an extension of Bertin's [7] visual matrix.

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Figure 14: Mackinlay's ranking of different visual variables for different tasks [36].

3 CHARACTERISTICS OF CHART VISUALIZATION ON HORIZONTAL DISPLAYS

Based on the literature, I have identified five main qualities of chart visualizations that are necessary for legibility on a tabletop. These characteristics are:

1. Appropriate data encoding system;
2. Alternative representation of data;
3. Support for arrangement and size of group;
4. Support for transition between personal and group work;
5. Easy orientation manipulation;

In this brief chapter I discuss existing techniques and interfaces that satisfy some these qualities and show where they fail to provide a balance of these essential attributes.

3.1 APPROPRIATE DATA ENCODING SYSTEM

The most critical attribute of information visualization is use of an appropriate data encoding system. A majority of the information visualization systems in tabletop use data encoding systems designed for traditional desktops. The perception of the encoding system can be affected if it is used in different system environments (for example horizontal displays [62]), which may affect the legibility of the visualization.

For tabletop environments, Wigdor et al. [62] conducted two studies whose results provided several recommendations for tabletop visualizations. Both studies show that the visual elements are more accurate and robust than others found in Cleveland and McGill [10]. The examination of these recommendations in tabletop interfaces and visualization is needed in order to validate their effectiveness.

3.2 ALTERNATIVE REPRESENTATION OF DATA

Another important attribute is different representations of the same data. This attribute becomes critical when considered for use in a collaborative workspace such as a tabletop. Zhang and Norman [63] proposed a theoretical framework of distributed representations for cognitive tasks. Their study concluded that allowing a variety of representations for the same information in co-located environments introduced a range and variation in cognitive activities. For example, when multiple users are collaborating, their task efficiencies differ from one another. In addition, the task complexity will not be the same for each of them. Users vary in their preference for viewing information. Providing the user with different representations to support single and multiple views can be beneficial for decision-making strategies. An example of this approach can be found in *Lark* [58] and the system for co-located collaboration work developed by Isenberg and Carpendale [25]. Both systems facilitate the coordination of interaction with information visualization. They provide the users with the ability to change collaboration styles and information representations. Such information representation needs to be validated in order to examine their usability. Gutwin and Greenberg [19] address how alternative layouts of interfaces impact the collaboration process. They have shown that in collaborative settings, group members benefit from alternative representations for data. For chart interfaces, this approach should facilitate the comprehensive process of graph reading, providing users with the ability to personalize the chart view and type based on their preference for fast and comprehensive interactions. One advantage of using this technique is to have flexible chart presentations for use in different scenarios.

3.3 SUPPORT FOR ARRANGEMENT AND SIZE OF GROUP

Location and size of group play an important role in the arrangement of shared artifacts on a tabletop. For a single user, orientation may not be a crucial problem since charts can be displayed and adjusted toward the user using different reorientation techniques. When group members collaborate on the same data (e.g., a chart) from different locations, the perception of group members will be affected. Different collaboration tasks may require different interactions and arrangements for each user. In some tasks, restriction and freedom of users' may or may not be required. Visual interfaces should adapt to either case. For example, when users stand shoulder-to-shoulder, chart visualization should provide an average point of view for each of the group members. When they are located at different positions, chart visualization should provide an optimal point of view where every group member has the same view. The use of a replicated copy approach may help to address the arrangement and size for group members when viewing a graph. However, this approach leads to other issues. When users have their own copy of the same chart, the work space is consumed. Interaction and manipulation techniques for adjusting the documents take most of the collaboration time. Ryall et al. [41] explored the effect of group size and collaboration with respect to the positioning of shared objects. They noticed that as the group size increases, the need for additional displays for shared information or multiple views in different orientations increases. Forlines et al. [18] found that when group members conducted a search on a horizontal display, group performance was higher than individual performance in terms of searching task accuracy.

3.4 SUPPORT FOR TRANSITION BETWEEN PERSONAL AND GROUP WORK

Another critical element in tabletop interfaces is to facilitate transition between personal and group workspace. During the collaboration process individuals share objects that are placed and spread around the tabletop. Orientation of objects in a tabletop is considered to be a human factor issue; it serves other purposes such as providing a means for coordinating and communicating among users [55, 30, 31]. Tabletop interfaces should support different objectives that assist the collaboration process such as establishing the intended group members, creating personal or public workspaces, and determining the ownership of an artifact on the tabletop [54, 31, 24, 26, 30]. Tabletop interfaces are also used as a temporary space where objects can be viewed in more detail. Tabletop interfaces should be simple to manage and able to organize the objects between personal and group spaces without consuming the available workspace on the tabletop.

3.5 EASY ORIENTATION MANIPULATION

Tabletop interfaces should provide comprehensive interaction techniques that support orientation, translation, and scaling for single users as well as for groups of individuals. Tabletops should make it simple to target the desired manipulation of a document using single touch-point and/or finger gestures.

3.6 SUMMARY

To summarize the discussion in this chapter, Table 1 lists how the techniques covered in Chapter 2 perform with respect to each of the characteristics that have been explained. For each characteristic, a subjective score based on my opinion of the availability of the characteristic is provided. The scores range from x to $\surd\surd\surd\surd$ and are categorized as follows:

x means that the tabletop interface is not sufficiently adequate;

$\surd$ means the interface has some features that support this quality; however, it is still not effective;

$\surd\surd$ means the interface has adequate support for the quality;

$\surd\surd\surd$ means that the interface provides very good support;

$\surd\surd\surd\surd$ means the technique supports the quality exceptionally well;

NA means the interface features are not available or unknown;

These ratings are purely subjective and serve only as a summary of the qualities provided by each technique. As the reader can see in Table 1, all existing interfaces are deficient in some respect for supporting all qualities. In Chapter 4, I examine the orientation effects of traditional graphs as well as the effect of applying the first two qualities on (appropriate data encoding and alternative representation of data) graphs before designing and implementing the OA-Graph interface.

Technique	Appropriate data encoding	Alterative representation	Arrangement of group	Workspace transition	Orientation Manipulation
DiamondSpin [44]	NA	×	√ √ √	√ √	√ √
Attribute Gates [52]	NA	×	√ √	√ √	√ √
InteracTable [49, 50]	NA	×	√ √	√ √	√
TeamTag [38]	NA	√	√ √	√ √	NA
ConnectTable [53]	NA	×	√	√ √ √	√
RNT [32]	NA	√ √	√ √	√ √ √	√ √ √
E-conic [39]	NA	×	√ √	√ √	√
2-D vector fields [15]	NA	×	√ √ √	√ √ √	√ √ √
Conversation Clock [27]	√	√	√	NA	NA
Lark [58]	√ √	√	√ √ √	√ √ √	√ √
Interactive Tree [25]	√ √	√	√ √ √	√ √ √	√ √

Table 1: Summary of techniques as they related to the five chart legibility qualities.

4

CHARACTERISTICS OF ORIENTATION AGNOSTIC VISUALIZATION

In this chapter, I present an experiment to investigate and evaluate chart readability in different orientations and the effect of orientation on the users' perception. The main objective was to gain an appropriate understanding of orientation issues, since it is essential to address these problems and consider a solution using the characteristics discussed in Chapter 3. Later I introduce and examine OA-Graphs in relation to the lessons learned from the experiment.

4.1 AN INVESTIGATION OF CHART ORIENTATION EFFECT ON TABLETOP

The main goal of this experiment was to investigate the impact of chart orientation on user perception in a tabletop setting. Readability performances were observed in terms of completion time and accuracy. This study and the results were published in [4].

4.1.1 *Hypotheses*

In order to explore the chart orientation issues, I came up with a number of hypotheses that direct the research focus as follows:

H1: When the chart is oriented in a different view other than the 0° angle, both completion time and error rate will increase.

H2: Chart type has an effect on completion time and error rate.

H3: The difference between a pair of points in the chart dataset has a significant effect on completion time and error rate.

H4: Chart orientation has significant interaction with chart type in terms of increasing the completion time and error rate.

H5: The difference between a pair of points in the the chart dataset has significant interaction with chart orientation and chart type in terms of completion time and error rate.

4.1.2 *Analytic task in information visualization*

Several taxonomies have been presented that summarize information visualization encoding systems and designs [7, 10, 36]. Amar et al. [5] observe different analytic activities and tasks that users may want to perform. In relation to charts, individuals perform various analytic tasks, from abstract to more detailed inquiries. For example, looking at financial charts, users may have an overview observation of all stocks and market behavior. Visualization of this information would be more abstract. A low-level visualization task is required when financial analysts look for specific stock behavior in a certain period of time. Amar et al. collected 200 low-level and high-level analytic tasks from groups of students who looked at a few data sets presented in charts. They categorized these analytic inquires into ten components: *Retrieve Value*, *Filter*, *Compute Derived Value*, *Find Extremum*, *Sort*, *Determine Range*, *Characterize Distribution*, *Find Anomalies*, *Cluster*, and *Correlate* [5]. In some cases, the analytic task can be a compound task meaning that it could be a combination of one or more of the primitive tasks.

I have chosen a task that requires searching and filtering to find predefined patterns. This task is commonly practiced by different financial analysts when viewing charts. This allows them to identify the pattern of the stock or peaks in a period of time. I introduced similar tasks to participants in the experiment. There were two types of patterns each participant had to identify in a chart.

In the first task, each participant was asked to compare all pairs of consecutive points in a chart to identify where the largest difference between two points occurred. Figure 15 demonstrates these two patterns. To illustrate, in a pair of two consecutive points, when the first point has a higher value than the second point, this pattern was called a decreasing pair. When the first point has a lower value than the second point, this pattern was called an increasing pair. In the chart provided to each participant, only one pair of points would have a highest (or maximal) increasing or decreasing pair.

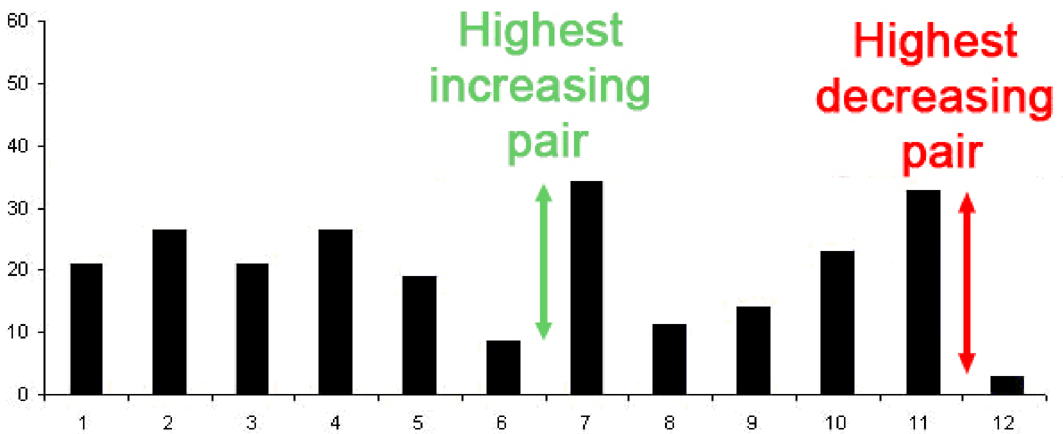


Figure 15: A chart could have one of two types of questions. Each participant was asked to identify the maximal decreasing (shown as points 11 to 12) or maximal increasing pair (shown as points 6 to 7).

4.1.3 *Charts*

The four most common chart types are used in the experiment. These charts are area, bar, line and scatter. They can be found in popular charting software. An algorithm has been used to randomly generate datasets for these charts. During the generation of the chart, the algorithm considers the differences between at least two pairs of points with 4, 6, or 10 pixel values. Four orientations were considered for charts in the experiment. Each chart type was oriented with an angle of 0°, 90°, 180°, and 270°. Figure 16 shows examples of the different orientations and chart types used in the experiment.

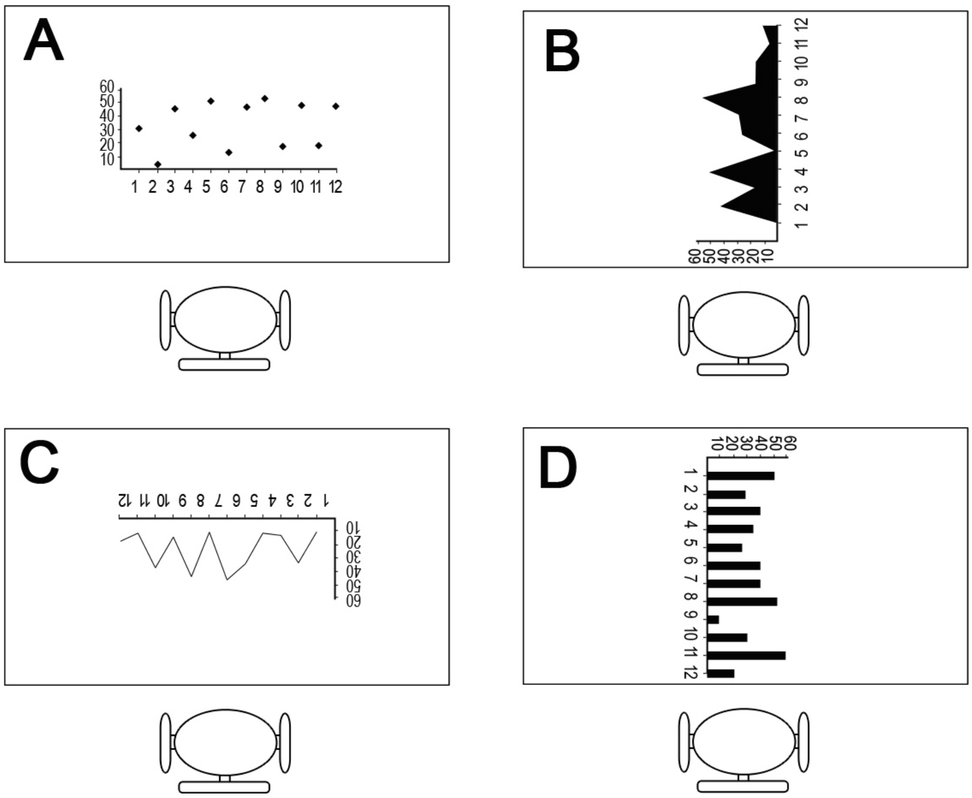


Figure 16: A bird's eye view of the tabletop showing different conditions that I used for four types of charts and orientation angles. Tabletop A is a Scatter chart with a 0° orientation. Tabletop B shows an Area chart with a 90° orientation angle. Tabletop C shows a Line chart with a 180° orientation angle. Tabletop D shows a Bar chart with a 270° orientation angle [4].

4.1.4 *Participants*

Forty undergraduate students (thirty-four male and six female) participated in the experiment. Subjects were not color-blind. Subjects were first-year university students with ages ranging from 21 to 35 years. The participants' experience in reading charts ranged from 0 to 5 years. Subjects were asked to sit on an adjustable chair at the center of a tabletop edge. The relative position and angle of the head for participants was not controlled. The reason for giving the subject freedom of head movement was to simulate real-world scenarios in collaborative settings. Each experiment session took around 30 to 45 minutes depending on individual performance.

4.1.5 *Apparatus and display configurations*

Participants were asked to sit on a chair at a height of 48cm so they would be facing a tabletop and used a mouse as the input device. The tabletop was positioned 80cm off the ground in a "landscape" orientation. The tabletop measured 153cm x 113cm. The projector contrast and brightness were adjusted to ensure that charts were shown in black and white. The projector resolution was set to 1152 x 864 pixels. The trial was considered complete when the subject answered a question related to a chart displayed on the tabletop.

4.1.6 *Task and stimuli*

The tabletop interface was implemented and used for this experiment. The interface contained four main components: chart, question, buttons, and timer. The chart dataset had eleven pairs of points. The question was related to the chart. The answer to the chart question was one of the eleven buttons referring to point pairs. A timer was used to keep the subject aware of the task completion time. The colour shown in the question depended on what was being asked. Red questions asked participants to find the highest decreasing pair. Green questions asked for the highest increasing pair. Before subjects ran the experiment, they were briefed on the task and were shown each type of chart with all the different possible orientations. During the practice session, each subject was given the opportunity to read the question and select an answer for each trial. At the end of each practice trial, the system interface provided feedback on accuracy. Subjects were allowed to practice more trials with different charts and orientations until they felt they understood the task requirements. During the experiment, each trial task lasted for a maximum of 40 seconds. If the subject did not select an answer during the 40 seconds, the trial was considered missed. When the timer reached the last 10 seconds, the timer background color turned red. The next trial appeared after the user made a selection or the timer expired. Each individual had to indicate one of the two patterns in a chart (highest increasing or highest decreasing pair) by clicking on the button that identified the correct pair of points for the question. Participants got a five-minute break in the middle of the experiment. The order used for displaying the chart orientation was counterbalanced to account for learning effects, making orientation order a within-subject control variable in the design. The experimental design can be summarized as:

40 participants ×
4 chart types ×
4 orientations ×
3 different difference values ×
2 trials (per condition)
= 3840 total trials.

4.1.7 *Results*

Normality assumptions for the univariate ANOVA were met. The results are organized by completion time and accuracy. I have used univariate ANOVA analysis which uses orientation, chart type, and difference in value as independent variables, and the completion time and accuracy as dependent variable. The Tamhane and Bonferroni [37] test was used for all post-hoc tests. Test statistic can be found in Appendix A.

4.1.7.1 *Completion time*

I used a total of 3034 trial points after I excluded outliers (-3 < std. dev.< 3) and wrong and missed trials for the analysis of completion time. Average completion time by orientation is shown in Figure 17.

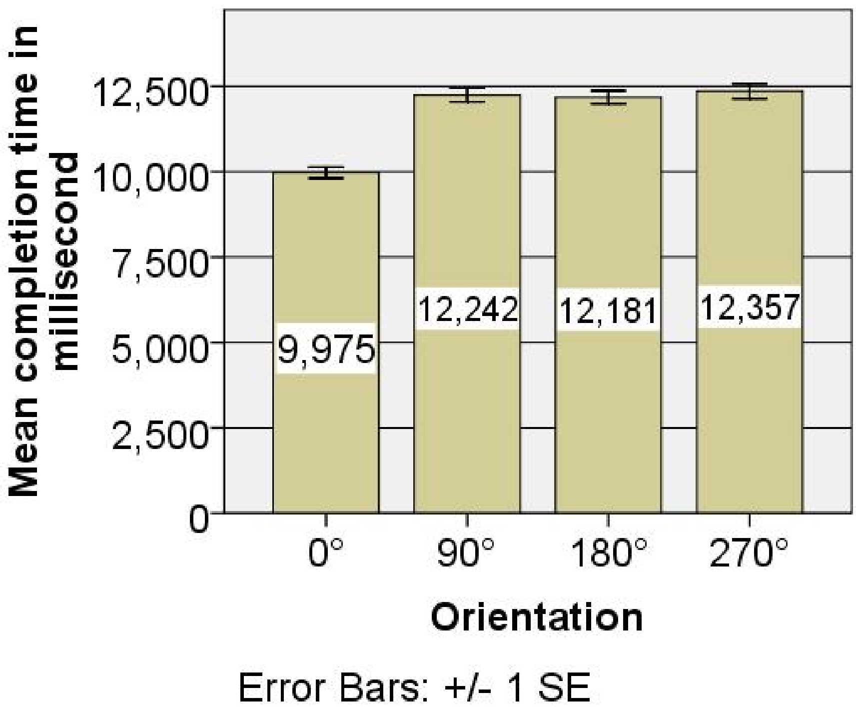


Figure 17: Average of completion times for charts with orientation angles 0°, 90°, 180°, and 270°.

In support for hypothesis H1, the analysis shows that chart orientation has a significant effect on completion time ($F_{3,117}$=68.401, p=0.001). The mean completion times 0°, 90°, 180°, and 270° were 9,975ms, 12,242ms, 12,181ms, and 12,357ms respectively. In addition, chart type turned to have a significant main effect on completion time ($F_{3,117}$=20.352, p=0.001). The mean completion times for area, bar, line, and scatter were 11,486ms, 11,523ms, 12,024ms, and 12,811ms respectively which is in favor of hypothesis H2. Another finding is that the difference in pairs had main effect on completion time ($F_{2,78}$=301.359, p=0.001). The mean completion time of 4, 6, and 10 pixels were 14,162ms, 11,361ms, and 10,065ms which supports hypothesis H3.

By looking at the interaction effects analysis, chart orientation turns to have an interaction with chart type ($F_{9,1251}$=4.294, p=0.001) with differences mainly occurring at the 90° and 180° angles. Also, chart orientation has an interaction with difference in value between pairs of points ($F_{6,834}$=3.976, p=0.001).

Further analysis of the result included pair-wise comparisons on chart orientation, chart type, and differences in pairs of points in charts. The pair-wise comparisons of chart orientation show different readability of certain chart orientations. Chart readability at 0° is significantly faster than all other orientations (all p=0.001). I did not find any significant differences between other orientations. The pair-wise comparisons of chart type indicated a significant differences in completion times for pairs in area and line graphs (p=0.004) and other graphs with scatter (p<0.05). The pair-wise comparison of differences between pairs of points in the charts had significant difference in terms of completion time. An increase in the difference between a pair of points resulted in decreases in completion time. This can be seen in Figure 18. When the maximal difference between point pairs was 10 pixels, subjects perform faster than at 6 and 4 pixels (both p=0.001). In the same manner, the subjects' completion time of 6 pixels was faster than 4 pixels (p=0.001).

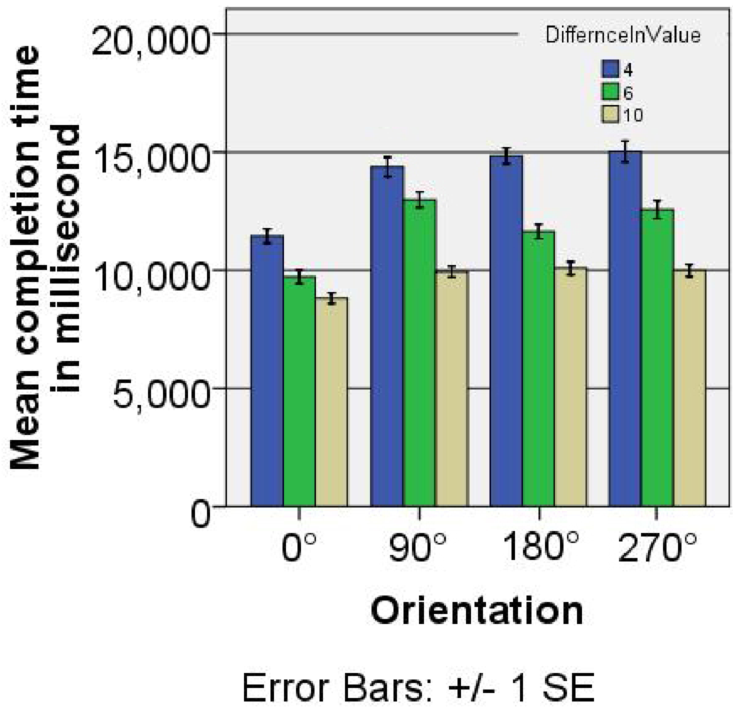


Figure 18: Average completion times for 4, 6 and 10 pixel maximal differences in pairs of points for chart orientation angles 0°, 90°, 180°, and 270°.

4.1.7.2 *Error rate*

Univariate ANOVA test showed the effect of orientation in terms of accuracy. In the favor of hypothesis H1, the test indicated that orientation had a significant effect on the error rate ($F_{3,11}$=5.550, p=0.001). The orientation angle of 0° had mean error rate of 0.15. For the orientation angle of 90°, the mean error rate was 0.20 while for the 180° orientation, the mean error rate was 0.22. The orientation angle of 270° had a mean error rate of 0.18 (Figure 19).

Also, there was a significant effect of chart type on the error rate which provides support for hypothesis H2 ($F_{3,117}$=36.096, p=0.001). The mean error rates for area, bar, line, and scatter chart types were 0.29, 0.16, 0.13, and 0.17 respectively. Moreover, the differences in values between pairs of points in a chart had a significant effect on the error rate ($F_{2,78}$=19.288, p=0.001). This supports hypothesis H3. The mean error rates for maximal point separation of 4, 6, and 10 pixels were 0.217, 0.203, and 0.149 respectively.

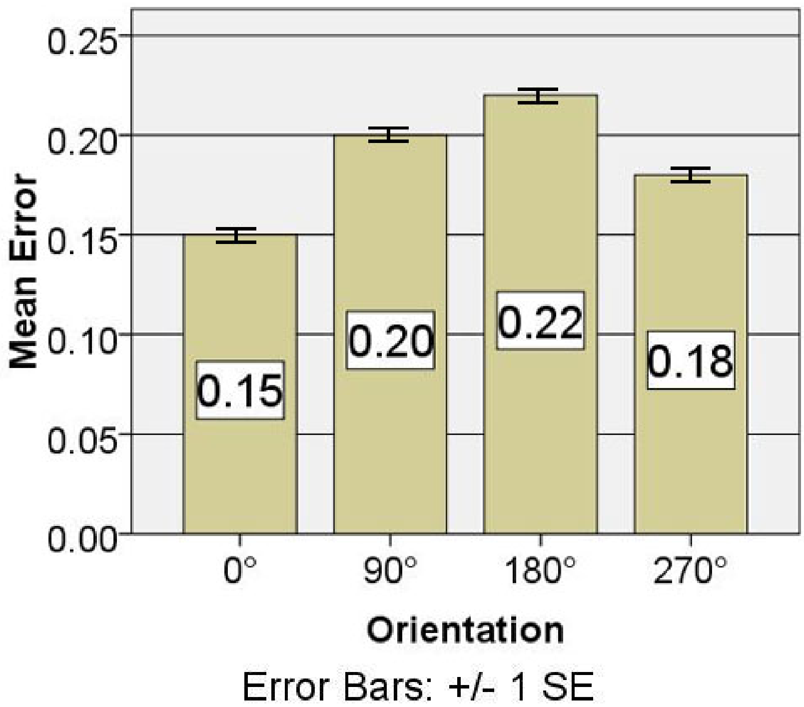


Figure 19: Average of error rate for orientation angles 0°, 90°, 180°, and 270°.

Interaction effects between independent variables were noticed: there was an interaction between chart orientation and chart type ($F_{9,1251}$= 13.772, p=0.001). Figure 20 shows the average error for the orientation by chart type interaction. These findings support hypothesis H4. In favor of hypothesis H5, there was significant interaction between chart orientation and difference in value in terms of error rate ($F_{6,834}$=21.805, p=0.001). Similarly, there was significant interaction between chart type and difference in value between pairs of points ($F_{6,834}$=18.570, p=0.001). The interaction between independent variables can be seen in Figure 21 and Figure 22.

Post-hoc pair-wise comparisons of chart orientations indicated significant differences in error rate. Error rate was significantly less at an orientation angle of 0° than when the angle was 90° and 180° (p = 0.04, p= 0.002). Between orientation angles of 0° and 270°, there was no significant difference (p = 0.573). Post-hoc pair-wise comparisons of chart type indicated significant differences in error rates. A higher error rate was found in the area chart type in comparison to line, bar, and scatter chart types (all p=0.001). No significant differences between the line, bar, and scatter chart types were found. Post-hoc pair-wise comparisons of differences in value between a pair of points only showed significant differences in error rate between 10 pixels and 4 pixels and 10 pixels and 6 pixels (all p=0.001, p=0.002).

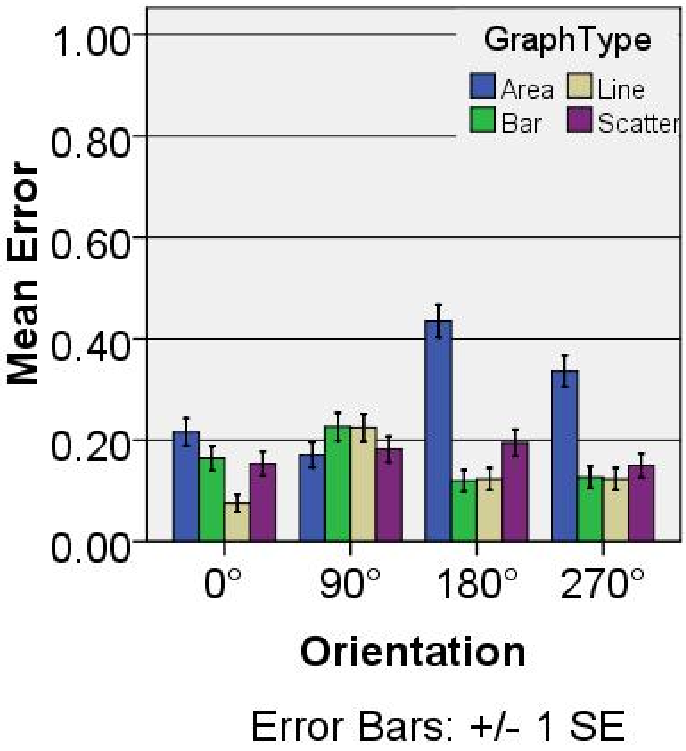


Figure 20: Average error rate for charts for orientation angles 0°, 90°, 180°, and 270°.

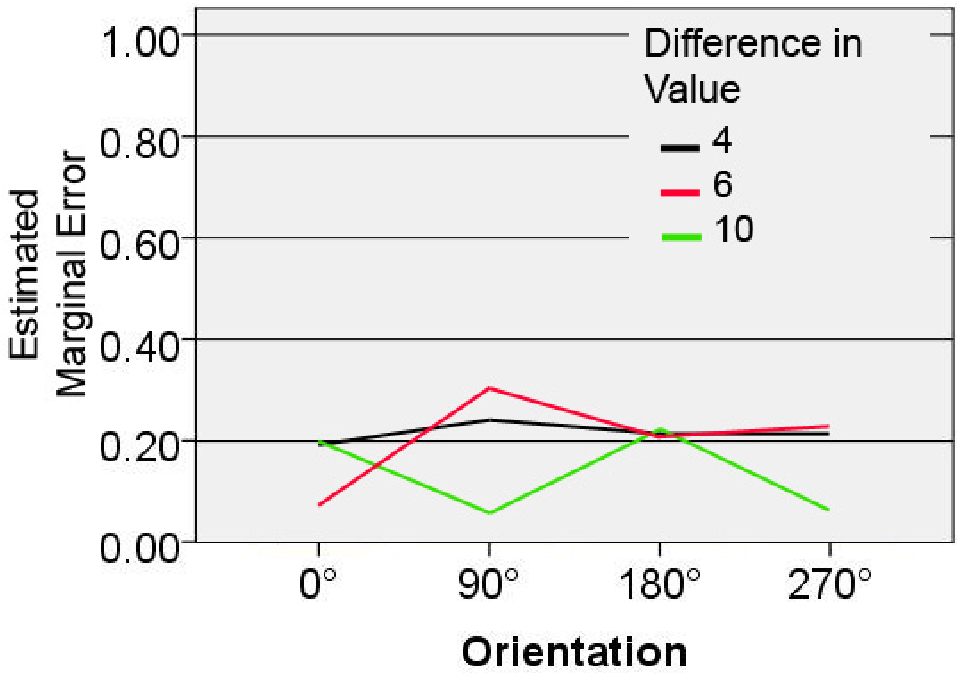


Figure 21: The mean error for four differences in pairs of points of size 4, 6, and 10 pixels for each orientation.

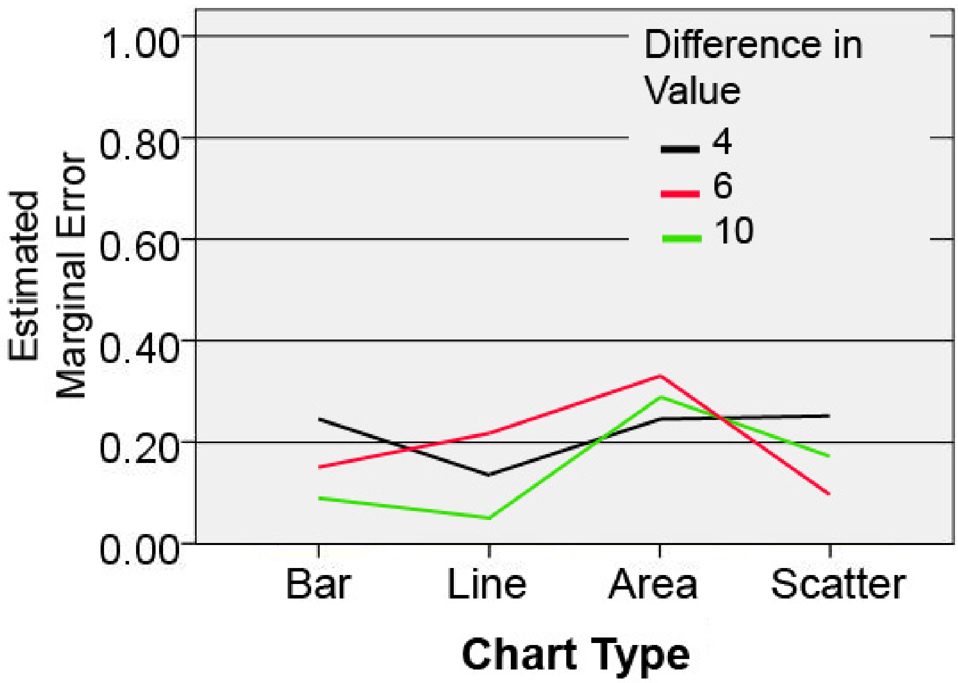


Figure 22: The mean error rate for four differences in pairs of points of size 4, 6, and 10 pixels for each chart type.

4.1.7.3 *Subjective rankings*

A post-study questionnaire, using Likert 5-point scales [34], was collected from participants asking them several questions in regard to orientation preference, performance, difficulties, and chart types preference in all orientations. The coding for the scale went from 1 (not preferred) to 5 (preferred). The questionnaire is provided in Appendix A.1.2. Users were asked to rate each orientation based on their preference. Looking at the questionnaire analysis, the result shows that 72% of users preferred 0° orientation to view graphs, which is the natural way users read charts. Users gave lower preferences to 90°, 180°, and 270° orientation due to their unfamiliarity with reading charts in such orientations. One observation made during the experiment was that some users tend to move their heads to adjust the chart view for linear chart styles. Allowing head movement during the experiment may explain the reason why most users rated 90° and 180° as neutral. Table 2 shows the user preference for each orientation. The second question asked users to assess how fast they believed they performed the task for each orientation. The results show that 65% of users thought their performance at 0° was the fastest among all orientations (Table 3). For 90°, 180°, and 270° orientations, users thought their performance was neutral. Users were then asked to rate the difficulty they had in reading the charts in each orientation. The analysis reveals that 0° was the easiest for 57% of users. Users rated the remaining orientations as 2, the rating between "very difficult" and "neutral" (see Table 4). One interesting feature was to see how users rated each chart type for all orientations. Table 5 shows that users preferred bar, line, area, and scatter charts, in that order.

	Orientation			
Rank	0°	90°	180°	270°
(not preferred) 1	0.0%	20.0%	12.5%	15.0%
2	0.0%	25.0%	32.5%	32.5%
(neutral) 3	10.0%	37.5%	35.0%	27.5%
4	17.0%	17.5%	17.5%	20.0%
(preferred) 5	72.0%	0.0%	2.5%	5.0%

Table 2: Users' preference for each orientation.

	Orientation			
Rank	0°	90°	180°	270°
(slowest) 1	0.0%	17.5%	10.0%	12.5%
2	0.0%	22.5%	22.5%	25.0%
(neutral) 3	20.0%	32.5%	30.0%	32.5%
4	15.0%	27.5%	27.5%	22.5%
(fastest) 5	65.0%	0.0%	10.0%	7.5%

Table 3: How fast users thought they performed in each orientation.

	Orientation			
Rank	0°	90°	180°	270°
(very difficult) 1	0.0%	5.0%	7.5%	7.5%
2	0.0%	47.5%	35.0%	40.0%
(neutral) 3	12.5%	32.5%	27.5%	37.5%
4	30.0%	15.0%	25.0%	15.0%
(easiest) 5	57.5%	0.0%	5.0%	0.0%

Table 4: How difficult users thought each orientation was.

	Chart Type			
Rank	Scatter	Area	Bar	Line
(not preferred) 1	30.0%	20.0%	2.5%	2.5%
2	40.0%	12.5%	10.0%	7.5%
(neutral) 3	10.0%	37.5%	17.5%	22.5%
4	7.5%	20.0%	25.0%	30.0%
(preferred) 5	12.5%	10.0%	45.0%	37.5%

Table 5: User preference for each chart type in all orientations.

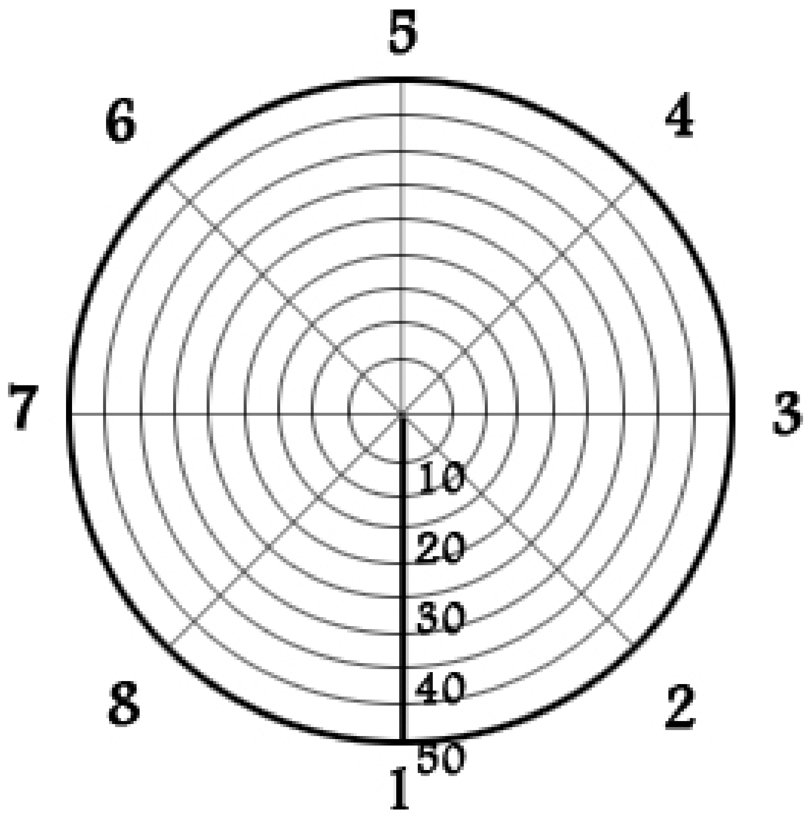
4.1.8 *Discussion*

The results of the experiment support all five hypotheses. The results showed that legibility of some of the most basic charts were affected by the orientation of the user around the tabletop. Generally, participants were capable of reading charts much faster and more accurately when they were presented at a 0° angle (or right side up) than at other angles, including 180° or upside down regardless of the differences between each chart type. This finding is supported by user feedback which showed that the desired orientation for the majority of users is 0°. These results support the findings of Wigdor et al. [62]. They have found that orientation affects our visual interpretation of primitive graphical elements. The majority of charts are encoded by primitive elements: whether this result would hold for higher orders of visual complexity is unknown. This would be an interesting direction for further research. A more interesting question is how to increase the legibility of charts regardless of user position around a shared surface using primitive elements.

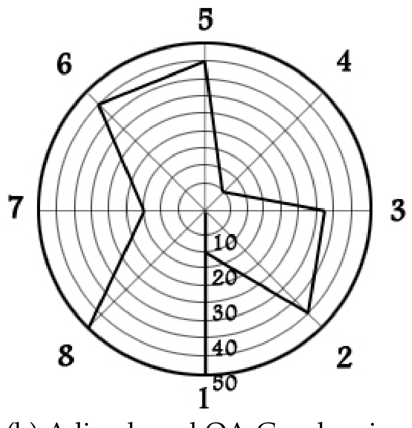
4.2 Design criteria of orientation agnostic graphs

The Orientation Agnostic Graphs, or OA-Graphs outlined in this thesis are designed to improve the legibility of simple graphs, such as charts, in difficult-to-read orientations. Reviewing earlier radial-based visualizations did inspire the design process of the OA-Graphs. Examples of radial-based visualizations are Hyperbolic Browser [33], Radial Tree [25], Radial Cladogram [58], and SunBurst [48, 58]. These visualization were not empirically examined for their legibility on horizontal displays. The reader is referred to Draper et al. [16] for more details on radial methods for information visualization. Although these visualizations are designed for single user and vertical displays, they have several interesting properties. One of the properties is that there is no implicit orientation compared to other common visualizations. Radial graph has no face that is right side up, which makes them suitable for addressing the type of problem I am investigating here. Furthermore, all points on the radius are equidistant to the centre of the graph which results in equal accessibility for users who are viewing the graph (with the exception of the constraints set by the physical structure of the table).

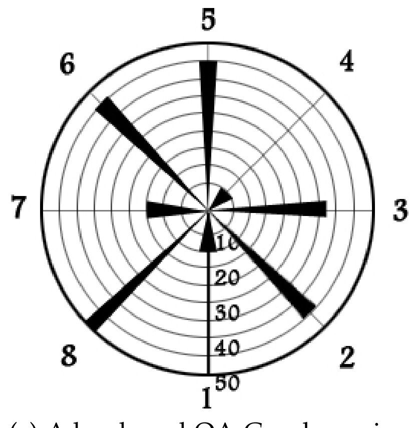
Considering the interesting properties mentioned above, the radial arrangement provides a flexible and ideal layout for placing items of interest. There are various OA-Graph designs to represent chart data using the above-described properties. An OA-Graph can be created simply by folding up a basic chart into a radial layout. Figure 23 shows the result of folding up basic chart axes. An outer line defines the point of reference. The chart values can be read in a counterclockwise manner. A line-based OA-Graph is analogous to the spidergram [47]. The different between a line-based OA-Graph and a spidergram is that spidergrams use different types of axes. Line and bar graphs were my initial investigation since they are commonly used and severely affected by orientation, as seen from the first experiment. As the finding from the first study and post-study questionnaire showed, bar and line graphs are more easily legible than area and scatter charts. This directed my interest to observer legibility of bar and line graphs when transformed into an OA-graph. Figure 23 b and Figure 23 c show examples of line-based OA-Graphs and bar-based OA-Graphs. With this layout, two different candidate designs can be considered: Reference-Out and Reference-In OA-Graphs as shown in Figure 24. In Reference-Out, the x-axis is defined by the outermost concentric ring. In Reference-In, the axis starts from the centermost point of the graph.



(a) The point of reference is at the centre and the graph is read counter-clockwise.

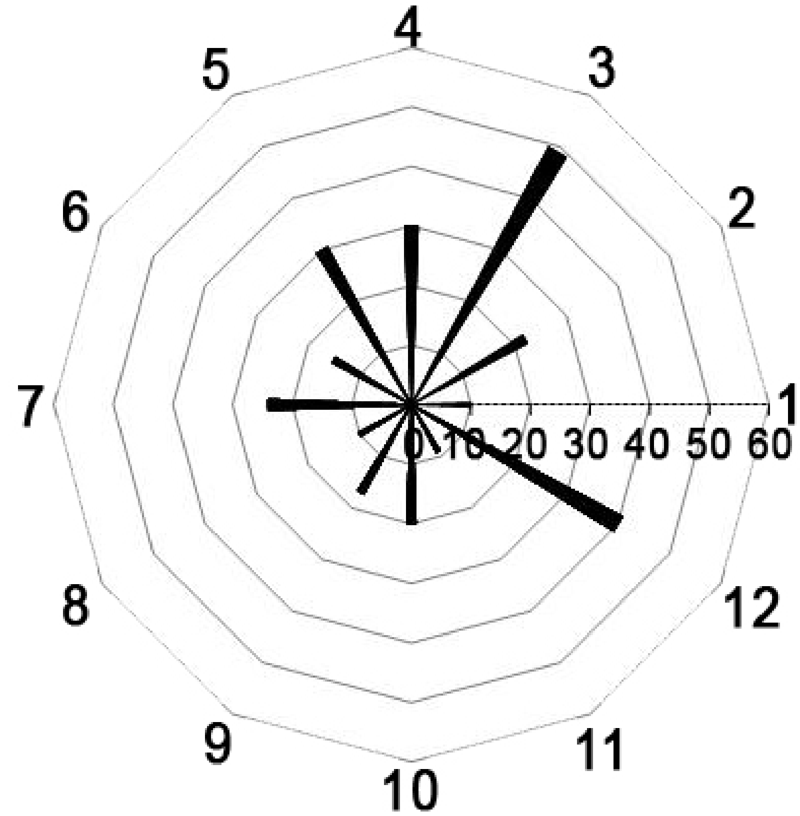


(b) A line-based OA-Graph using the same layout in (a).

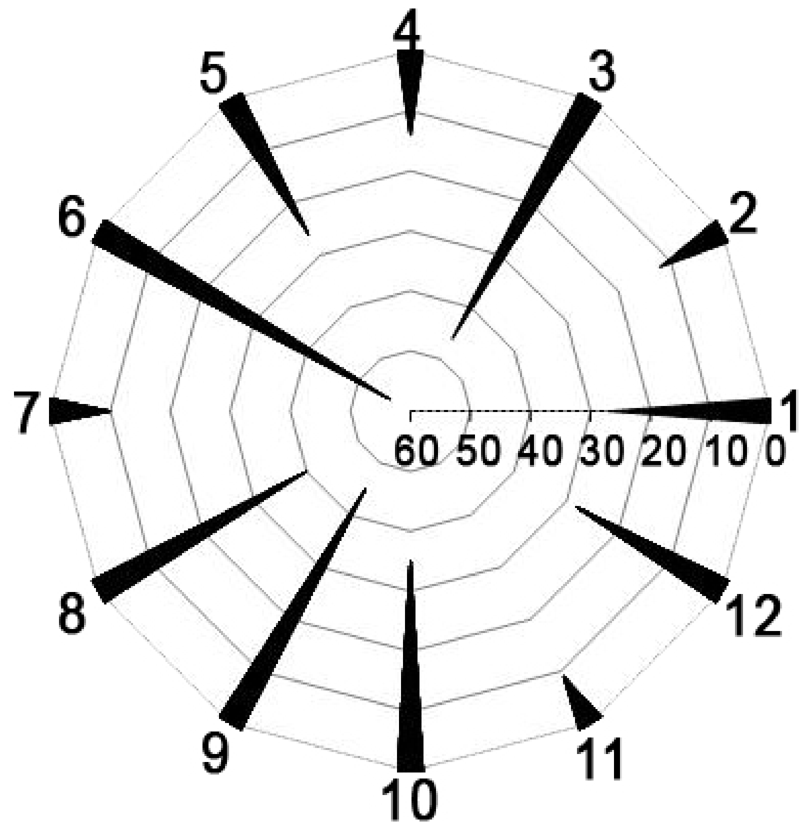


(c) A bar-based OA-Graph version of the same dataset in (b).

Figure 23: The design of an OA-Graph is based on a transformation of traditional graphs into a radial layout.



(a) A Reference-In OA-Graph: The graph plots the value of each category along a separate axis that starts in the centre of the chart and ends on the outer ring.



(b) A Reference-Out OA-Graph:The value of each category is along a separate axis that starts in the outermost ring of the chart and ends in the centre of the chart.

Figure 24: Two types of OA Graphs: Reference-Out and Reference-In.

4.3 effect of orientation agnostic graphs in tabletops

The main objective of the second experiment was to evaluate reference in and reference out OA-Graphs. To achieve this goal, I compared traditional graphs against the OA-Graphs in terms of their effect on user perception. All users have equal views of the OA-Graph, regardless of their position around the table. This gives OA-Graphs an advantage over linear graphs. Completion time and accuracy were measured to record readability performances. The second experiment used the same searching and filtering tasks as outlined in the first experiment. Subjects were asked to identify predefined patterns in an OA-Graph. The first experiment configurations were used in the second experiment.

4.3.1 *Hypotheses*

To focus my preliminary exploration of the issues, I formulated the following hypotheses:

H1: OA graphs perform better than traditional graphs that are orientated at 180° for user completion time and error rate.

H2: The relative difference between a pair of points in a linear graph and an OA-Graph has a significant effect on completion time and error rate.

H3: Using bar and line chart types in linear and OA-Graphs will have an effect on completion time and error rate.

4.3.2 *Participants*

Thirty subjects (twenty male and ten female, participated in the experiment. Subjects were first-year and fourth-year university students with ages ranging from 18 to 30. I measured the display view angle from the centre of the tabletop (see Figure 1). I used the right-angled triangle formula (Tan θ = Opposite / Adjacent). Opposite is the distance from the edge of the tabletop to the user's eye. Adjacent is the distance from the edge of the tabletop to the centre of the tabletop. fifteen subjects were asked to do the experiment while standing; their view angles ranged from 21° to 30°. The rest of subjects were asked to do the experiment seated; their viewpoints ranged from 41° to 50°. Subjects, who did the experiment seated, sat on adjustable chairs in the centre of the tabletop edge at a height of 48cm in front of the tabletop. Each experiment session lasted 30-48 minutes depending on the performance of the participant.

4.3.3 *Charts*

Two types of charts and two orientations were used to compare linear charts with OA-Graphs: the bar and line chart types and 0° and 180° for chart orientation. For the chart type, bar and line charts were chosen for their good performance in terms of completion time and accuracy as the first experiment showed. For the OA-Graph, I have used bar-based and line-based OA-Graphs. To examine chart performance in best/worst reading scenarios as shown by analysis of the first experiment, two orientations (0° and 180°) were chosen. Both types of OA-Graphs, Reference-In and Reference-Out, were evaluated as shown for a bar-based OA-Graph in Figure 24. An algorithm was used to randomly generate a traditional chart style. The OA-Graph was then created using the same data. The traditional charts and OA-Graphs were generated with consideration for differences in value between at least two pairs of points with 4, 6, or 10 pixels. For traditional charts, both the line and bar charts were oriented with an angle of 0° and 180°.

4.3.4 *Task and procedure*

The second experiment used the same tabletop interface and components as the first experiment. Users were introduced to traditional and OA-Graphs to enhance their familiarity with reading the variations of OA-Graphs. All participants took practice sessions to make them familiar with the task. Each trial was timed to last 40 seconds. The next trial appeared when the user chose an answer or the timer expired. Each participant had to identify a chart pattern and then click on the correct pair of points listed for the question. In the middle of the experiment, there was a five-minute break. The presentation order for the various chart orientations was counterbalanced to account for learning effects, making orientation order a within-subject variable in the experimental design. The experimental design can be summarized as:

30 participants $\times$
2 chart types (bar, line) $\times$
4 orientations (0°, 180°, Reference-In, Reference-Out) $\times$
3 different values (in pixels) for point spacing (4, 6, 10) $\times$
3 trials (per condition)
= 2160 total trials.

4.3.5 *Results*

Normality assumptions for the univariate ANOVA were met. The results of the second experiment are organized by completion time and accuracy. A univariate ANOVA was applied to the average completion time and error rates using orientation, chart type, difference in value, and subject standing or seating as independent variables and completion time and accuracy as dependent variables. The Tamhane and Bonferroni [37] test was used for all post-hoc tests.

4.3.5.1 *Completion time*

I used a total of 1846 trials after excluding outliers (-3 < std. dev. < 3), missed, and wrong trials. In favor of hypothesis H1, the analysis indicated that orientation has a significant effect on completion time ($F_{3,87}$=115.302, p=0.001). Also, the analysis revealed that both OA-Graphs (Reference-In and Reference-Out) performed better than traditional charts when the orientation angle was 180°. They performed slightly worse than traditional charts when the orientation angle was 0°. The mean completion times for orientation are shown in Figure 25. The maximal range of values of point pairs had a main effect on the completion time ($F_{2,58}$=257.022, p=0.001) which supports hypothesis H2. When the difference in pairs of points was 4 pixels, participants used more time to complete the task. As the range of values increased, the completion time of the task decreased. The mean completion times for the 4 pixel, 6 pixel, and 10 pixel point pair differences were 11,877ms, 10,736ms, and 9,269ms respectively.

I was interested in seeing the effect of chart types on participant performance. I anticipated a similar performance between bar and line chart types in all orientations as Experiment 1 revealed. However, chart type turned out to have a significant main effect on the completion time ($F_{1,29}$=27.728, p=0.001). The mean completion times for the bar and line charts were 10,380ms and 10,874ms respectively. Another interesting variable is the effect of the view angle of a chart on the completion time. It helped to determine whether it is better to view a chart while standing or seating. The results indicated that there was a significant main effect of view angles of charts on the completion time ($F_{1,29}$=8.427, p=0.004). The group of participants who performed the experiment while standing had a mean completion time of 10,491ms, while the group who did the experiment seated had mean completion time of 10,764ms.

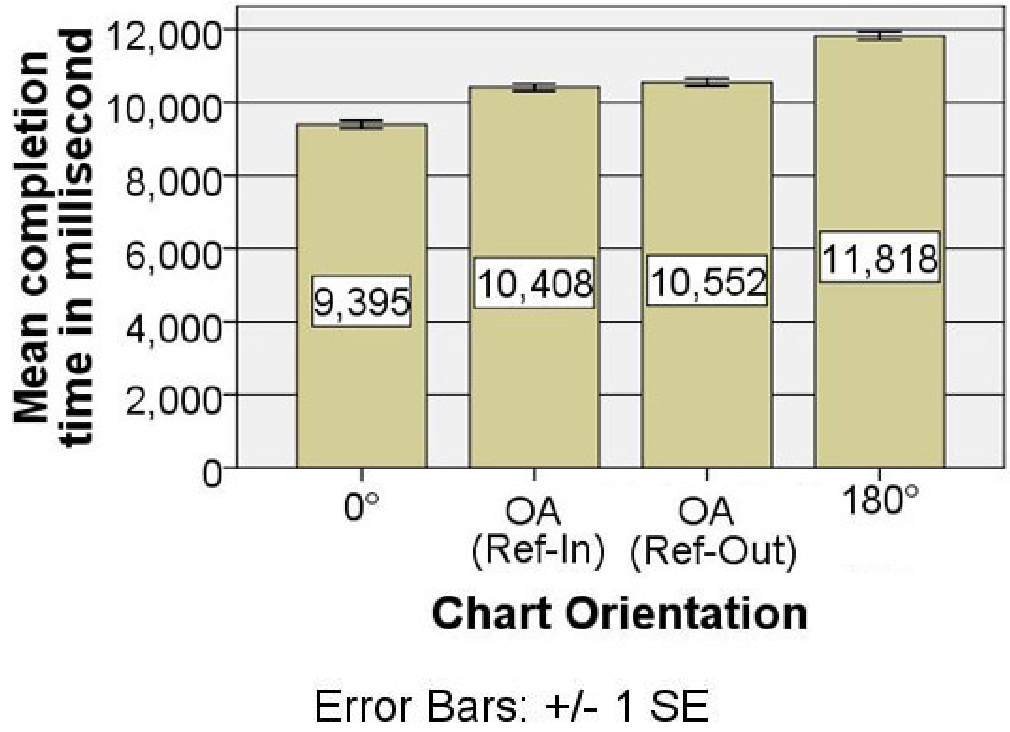


Figure 25: Average completion times for both chart types for angles 0°, Reference-In OA-Graph, Reference-Out OA-Graph, and 180°.

In terms of the interaction effects between independent variables, chart orientations do not interact with chart type. Interestingly, chart orientation does have interaction with the user's platform (either standing or sitting) ($F_{3,87}$=4.558, p=0.003). A summary of the interaction between chart orientation and the user's platform can be seen in Figure 26. Additionally, it was found that chart type significantly interacts with differences in the value between pairs of points ($F_{6,174}$ =11.370, p=0.001).

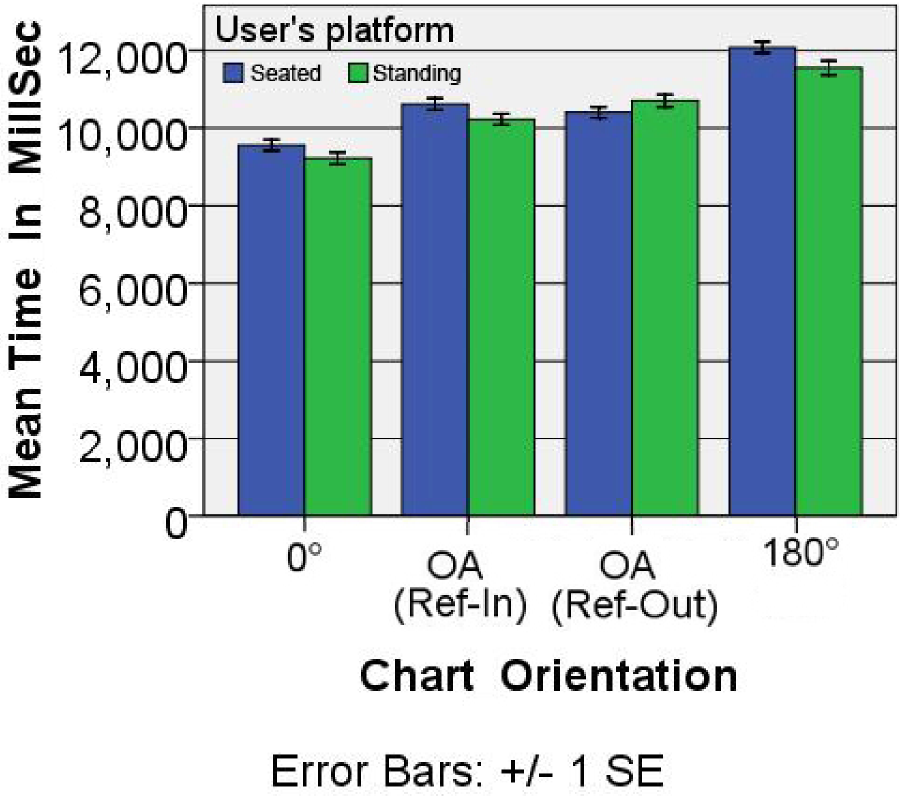


Figure 26: Average completion times for chart orientation for angles 0°,Reference-In OA-Graph, Reference-Out OA-Graph, and 180° by user platform (seated or standing) .

Post-hoc pair-wise comparisons of orientation yielded significant differences (all $p < 0.001$) in task completion time for all pairs. The pair-wise comparisons showed that participants were faster at reading charts at an orientation angle of 0° than the OA-Graph (Reference-In), OA-Graph (Reference-Out), or the linear graph with an orientation angle of 180°. Also, Reference-In and Reference-Out OA-Graphs have better legibility (both $p < 0.001$) than the upside-down graph. Post-hoc pair-wise comparisons of the maximal difference in pair values chart show significant differences in completion time (all $p<0.001$) for all pairs of points at 4, 6, and 10 pixels, a similar pattern as in the first experiment.

4.3.5.2 *Error rate*

A total of 2111 trial data points were used in the analysis after outliers were removed (-3 < std. dev. < 3). The ANOVA test indicated significant main effects of orientation, chart type, and difference in value. The orientation had a significant effect on the error rate which supports hypothesis H1 ($F_{3,87}$=6.610, p=0.001). The mean error rates for 0°, Reference-In OA-Graph, Reference-Out OA-Graph, and upside down (180°) were 0.08, 0.12, 0.13, and 0.17 respectively as shown in Figure 27. The user's platform turned out to have no effect on the error rate.

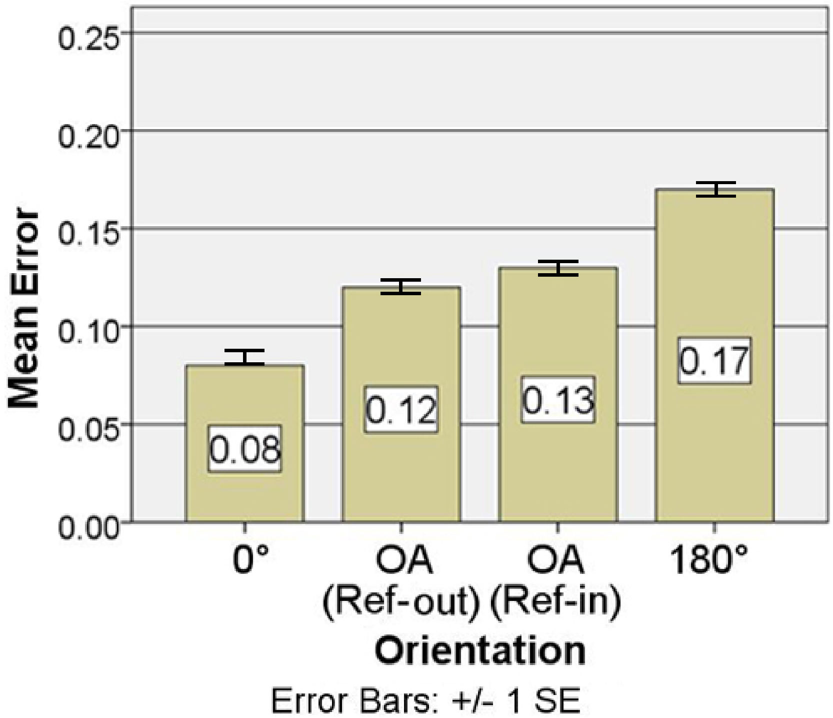


Figure 27: Average error rate for charts with four orientation angles: 0°, OA (Reference-In), OA (Reference-Out), and 180°.

There was a main effect of differences in point pairs in a chart on the error rate ($F_{2,58}$ =31.891, p=0.001). The analysis showed negative correlation between differences in point pairs and the error rate: the higher the value of at least one pair of points, the lower the error rate. I also noticed that there was a significant effect of the chart type on the error rate ($F_{1,29}$ =15.888, p=0.001). The mean error for bar and line charts were 0.099 and 0.155 respectively, which allows the rejection of hypothesis H3 in terms of the error rate. The viewpoint of the chart has no significant effect on the error rate ($F_{3,87}$=0.426, p=0.514).

A pair-wise comparisons analysis of orientation showed that the chart with orientation angle 0° was not significantly better than both Reference-Out (p=0.094) and Reference-In (p=0.281) OA-Graphs. This is an interesting finding considering that the view with OA-Reference-In is slightly more distorted than the right-side up view. Similar pair-wise comparisons analysis of chart type indicated a significant difference in error rate. The line chart has a higher error rate, with a mean of 0.155, than bar charts, with a mean of 0.099 (p=0.001). Finally, maximal difference in pair values chart has an effect on the error rate. When the maximal difference in pair values chart was a 4-pixel variance, the error rate was higher than both 6 pixels and 10 pixels (All p<= 0.049).

4.3.5.3 *Subjective rankings*

A post-study questionnaire, using Likert 5-point scales [34], was answered by participants. They were asked several questions in regard to orientation preference, performance, difficulties, chart type preference for 0°,OA-Reference Out, OA-Reference In, and 180°. The coding for the scale was similar to the coding for the post-study questionnaire of Experiment 1. The questionnaire is provided in Appendix A.2.2. Users were asked to rate each orientation based on their preference. The analysis of the first question shows that 63.3% of users prefer 0° to view the chart whereas none of the users prefered to view the chart in 180°. Also, 3.3% and 13.3% of users prefer Reference Out and Reference In OA-Graph respectively. This may indicate that users become familiar with OA-Graphs and find them suitable to use. More details of user preferences for orientation are shown in Table 6. Looking at the questionnaire analysis of how fast users were in each orientation, 46.7% and 3.3% of users thought they were fast at 0° and Reference In OA-Graph respectively. Table 7 shows how fast users felt they were in each orientation. Interestingly, 33.3% of users rated their preference for 180°, Reference-Out OA, and Reference-In OA to be neutral.

In terms of orientation difficulties, 53% of users found 0° orientation to be the easiest. 36% of users rated 180° orientation as 2 (between very difficult and neutral). 46.7% and 40.0% of users found Reference-Out OA-graph and Reference-In OA-graph to be neutral. More details can be found Table 8. While observing users during the experiment, I noticed the amount of head movements decreased significantly when using OA-Graphs. This may support the feedback from the questionnaire.

The last question was aimed at finding whether bar or line formats affect the complexity of tasks. Users were asked to rank bar or line graphs based on how difficult they felt they were for all four orientations. By looking at Table 9, there is no significant difference between bar and line graph for linear charts. The majority of users (30%) rated bar graphs as neutral whereas 23.3% of users rated line graphs as neutral. The same percentage of users (23.3%) rated bar and line graphs as their preference. For Reference-Out OA-Graph 46.7% of users rated bar graphs to be neutral while only 20% of users rated line graphs as neutral. Also, only 6.7% did not prefer bar graphs while 26.7% of them did not preferred line graphs. For Reference-In OA-Graph, users seemed to feel equally comfortable with both bar and line graphs, giving them similar ratings. Table 9 shows the users ratings for bar and line graphs.

	Orientation			
Rank	0°	180°	Reference-Out OA	Reference-In OA
(not preferred) 1	0.0%	20.0%	23.3%	10.0%
2	0.0%	33.3%	30.0%	36.7%
(neutral) 3	13.3%	43.3%	26.7%	23.3%
4	23.3%	3.3%	16.7%	16.7%
(preferred) 5	63.3%	0.0%	3.3%	13.3%

Table 6: User preferences for each orientation.

	Orientation			
Rank	0°	180°	Reference-Out OA	Reference-In OA
(slowest) 1	0.0%	20.0%	20.0%	16.7%
2	0.0%	30.0%	30.0%	36.7%
(neutral) 3	10.0%	33.3%	33.3%	33.3%
4	43.3%	16.7%	16.7%	10.0%
(fastest) 5	46.7%	0.0%	0.0%	3.3%

Table 7: How fast users thought they performed in each orientation.

	Orientation			
Rank	0°	180°	Reference-Out OA	Reference-In OA
(very difficult) 1	0.0%	16.7%	20.0%	10.0%
2	0.0%	36.7%	26.7%	26.7%
(neutral) 3	13.3%	23.3%	46.7%	40.0%
4	33.3%	23.3%	6.7%	23.3%
(easiest) 5	53.3%	0.0%	0.0%	0.0%

Table 8: How difficult users thought each orientation was.

	Chart Type					
	Linear chart		Reference-Out OA		Reference-In OA	
Rank	Bar	Line	Bar	Line	Bar	Line
(not preferred) 1	6.7%	16.7%	6.7%	26.7%	0.0 %	0.0%
2	13.3%	16.7%	16.7%	20.0%	13.3%	10.0%
(neutral) 3	30.0%	23.3%	46.7%	20.0%	33.3%	36.7%
4	26.7%	20.0%	16.7%	23.3%	40.0%	40.0%
(preferred) 5	23.3%	23.3%	13.3%	10.0%	13.3%	13.3%

Table 9: The result of how difficult users thought each orientation was.

4.3.6 *Discussion*

The results support all of the hypotheses except hypothesis H3 for the error rate. I found that the legibility of some of the most basic charts is affected by user orientation around the tabletop. While some differences exist between each chart type, in general, participants were capable of reading charts much faster and with fewer errors when presented at a 0° angle (or right-side up) than at the other angles, including 180° or (upside down). These results corroborate, and can partly be explained, by the findings of Wigdor et al. [62] that orientation affects our visual interpretation of primitive graphical elements. Since most graphs are created based on a composition of primitive elements, it is interesting to see this result hold for higher orders of visual complexity. The study shows that OA-Graphs perform better than 180°. It is interesting to see that participants learned how to read OA-Graphs after the practice session. The user survey shows that a high percentage of individuals became familiar with OA-Graphs. The study confirms that the best orientation for a user in a tabletop setting is 0°. When there are needs for collaboration or sharing information, OA-Graphs can reduce the effect of orientation. What remains to be known is whether basic charts can be created in a manner to increase legibility regardless of user position around a shared surface.

5

ORIENTATION AGNOSTIC GRAPH INTERFACE

5.1 IMPLEMENTATION

In this chapter, I describe the integration of the findings on the legibility of common charts at different orientations, and how OA-Graphs can be interacted with on a multi-touch tabletop interface. I consider the use of the interface for both a single user environment and for a group of users. An interaction technique that gives tabletop users the ability to interact with visualizations and share a common view for collaborative tasks is described.

5.2 TABLETOP SETTING

User interactions, for example, touching and moving objects in the display, were captured using a vision-based multi-touch display. Diffuse illumination and a camera are used to capture user touch. The system then processes and filters captured images based on predefined interaction patterns. A multi-touch tabletop that uses Frustrated Total Internal Reflection (FTIR) as an input device is used to support multi-touch input from users around the tabletop. Figure 28 shows a simplified view of the setup and architectural design of FTIR. The concept behind a FTIR multi-touch display is that when IR LED light travels through acrylic at a specific angle, the light continues to reflect internally in the edge of acrylic. If an object, for example, a finger, touches the acrylic on the top, the light ray partially bounce and will be refracted at the boundary surface and then reflect the ray toward the mirror. An infrared web camera is used to capture the light spots in the acrylic and pass it to the image detection algorithm that identifies and tracks changes in the image. I have used PyMT [22], an open source library for developing multi-touch applications, to process captured touch location coordinates and map them to the graph visualization interface. Python is the programming language used to implement an OA-Graph widget. This widget supports multi-touch interaction and gestures. Figure 29 shows the OA-Graph widget and interface.

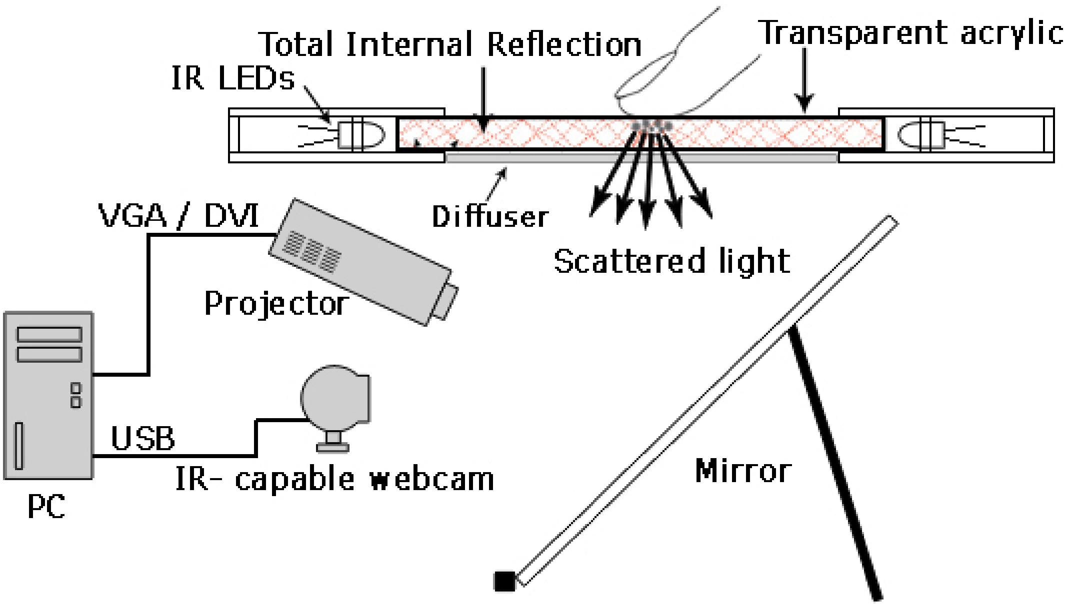


Figure 28: The architecture of the Frustrated Total Internal Reflection tabletop used to implement the graph visualization interface.

5.3 INTERACTION TECHNIQUES

I have developed interaction techniques to manipulate OA-Graphs with consideration for two main objectives. The first objective is to provide tabletop users with the ability to switch between alternate presentations of a chart during a collaborative task. For example, when a user wants to share a chart with other users, in order to have an optimal view for all users, she could enable a mode that changes the chart presentation from a linear style to orientation agnostic style. The second objective is to allow tabletop users to interact and manipulate the orientation of a chart to make it right side up toward any one of the other users around the table. I also considered providing common interaction techniques such as translation, orientation, and scaling of OA-Graphs. The concept of supporting these objectives is to reduce the effect of orientation by providing an optimal view of a chart for a group of users collaborating on a flat tabletop display.

Figure 29: OA-Graph interface that support multi-touch and personal and group workspaces.

5.4 ORIENTATION AGNOSTIC REPRESENTATION

The conducted experiments have shown that OA-Graphs perform better than linear charts with an orientation angle of 180° and perform slightly worse than linear charts with an orientation angle of 0°. Providing the user with the ability to switch between different representations to support single and multiple views can be beneficial. In this technique, a user can make a simple gesture on the chart to be able to modify the representation and the view angle of a chart, as the next section shows.

5.5 SWITCHING BETWEEN DIFFERENT GRAPH STYLES

Most tabletop interfaces display graphs upright since GUI widgets are oriented in a single direction. This is usually convenient for the person seated at the bottom edge of the display. Some studies have proposed different orientation techniques to address the need for users to reorient an object every time other users need to have the best view angle for it (refer to Chapter 2). My technique solves this issue by using a simple gesture to change the view to an OA-Graph which will give all users the same view all around a tabletop. A single circled finger gesture invokes a 'graph style' mode, allowing the user to switch between linear and OA-Graph styles (see Figure 30). It is worth mentioning that I considered changing between graph modes using a compelling and communicative gesture to engage or disengage group collaborative interest. For example, when a user wishes to share a chart with others in the group, a circular gesture on the chart could be a signal to begin or end a collaborative session. Users can invoke it to establish and maintain individual and group workspaces [33, 31]. Graph styles can be used to determine the state of a graph to be public (OA-Graph) or private (linear graph) to other users. When a user wants to share the chart with other users in a tabletop setting, a simple circle gesture changes the graph from linear to OA and vice versa.

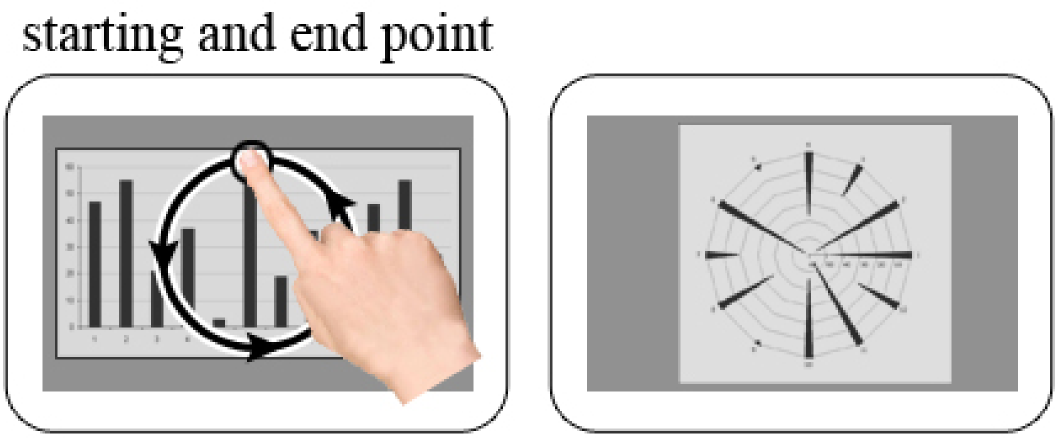


Figure 30: A user can easily switch between different graph styles using a single fingered gesture. When the user wishes to share the graph with other users she draws a circle shape on the graph and the interface will recognize the gesture and change the graph into an OA-Graph (shown on the right).

5.6 graph type and orientation manipulation

5.6.1 *Graph type*

Feedback from participants in both experiments as well as the experimental results show that graph type has an effect on the completion time. I considered providing users with the ability to change between different types of graph based on their preference. One advantage of using this technique is to have flexible chart presentation for different scenarios. For example, one scenario could be when a user wants to share a graph with others using a robust graph type such as a bar graph. Another scenario could be choosing the graph type based on user preference. Users can use three single-finger gestures that invoke a different type of graph representation (bar, line, and scatter). The gestures are a simulation of the first letter of each of the three types of graph. Gestures can be applied from any location around the tabletop. When a user wants to change from one graph chart to another, a gesture is used to invoke the desired graph type (see Figure 31). This technique is applied for both linear and OA-Graph styles.

Figure 31: The interface provides the user with ability to choose different chart types (line, scatter or bar) for representing a graph. The user makes a finger gesture from the starting point (1) to the ending point (2) to invoke the change.

5.6.2 *Graph orientations*

Experimental analysis indicates that a chart is best viewed when it is oriented toward a person located at any edge of the display. OA-Graph interface provides a single finger gesture to invoke a quick change in the orientation of a chart toward any tabletop edge. The gesture starts from the user side and ends on the desired side of the tabletop. To illustrate, if a user wants to orient a graph to 180°, a gesture consisting of a vertical straight line from the middle of the graph to the upper side of the graph can be entered to invoke the reorientation (see Figure 32). These interaction techniques can be used not only in triangular tabletops but also in circular tabletops. The algorithm calculates the angle between the center of the widget and the end point location of the gesture.

5.6.3 *Translate, orient, scale*

During collaboration activities, translating, orienting, and scaling are important interaction mechanisms that allow users to organize charts on a tabletop interface. The graph container on the tabletop interface provides these techniques to enrich the manipulation of graphs and assist in the interaction process.

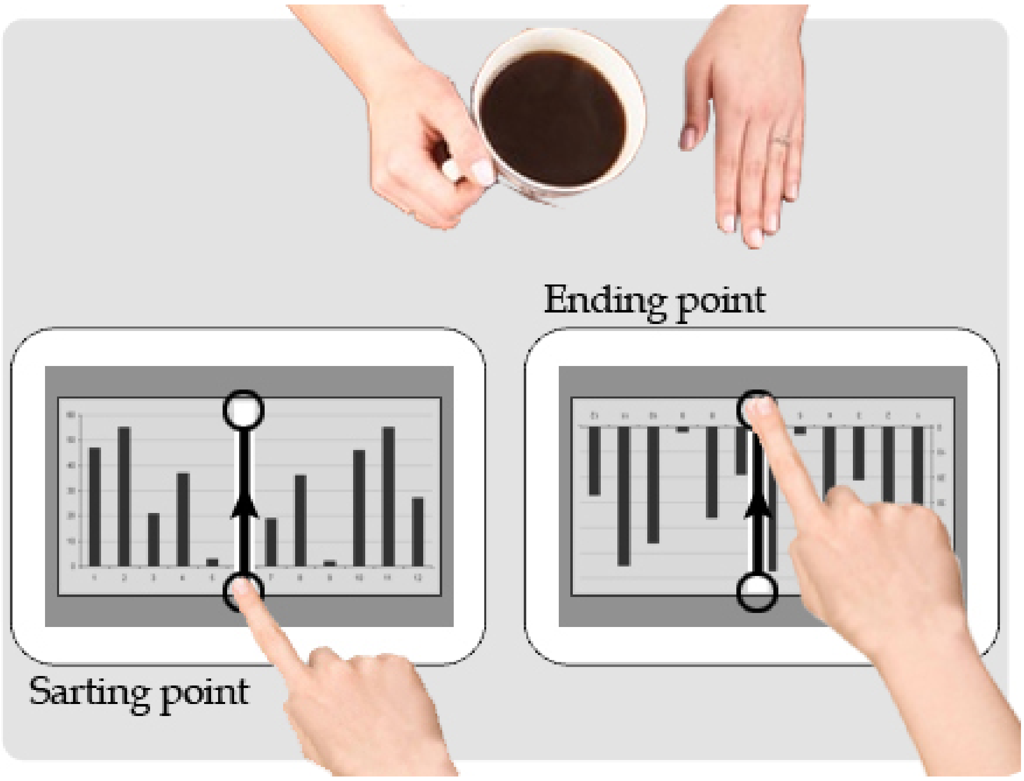


Figure 32: A finger gesture is used to invoke a quick change in the orientation of a chart toward any tabletop edge.

5.6.4 *Personal and group territories*

I have considered both group and personal territories when designing the graphical interface. I use the centre of a graph user interface working area as a group territory. Activities such as manipulating and discussing graphs are typically performed in the group territory. Personal territories allow users to disengage from group activities as well as reserve space in front of them for their own personal activities. When a user wants to have their own copy of a graph with their best view toward them, they can move the chart toward the edge where they are located and the system will make a copy of the chart in their personal territory. This allows other users to make use of the original copy of the chart for group activities. Most of the time, personal territories take space away from the total space available for a group territory. This leads to a reduction of the amount of information that can be presented. To offset this problem, personal territories can be manually adjusted so that a user can hide their personal space to increase the space available for the group territory. Users can hide their personal territory by touching a tab located at the edge of their area (see Figure 33).

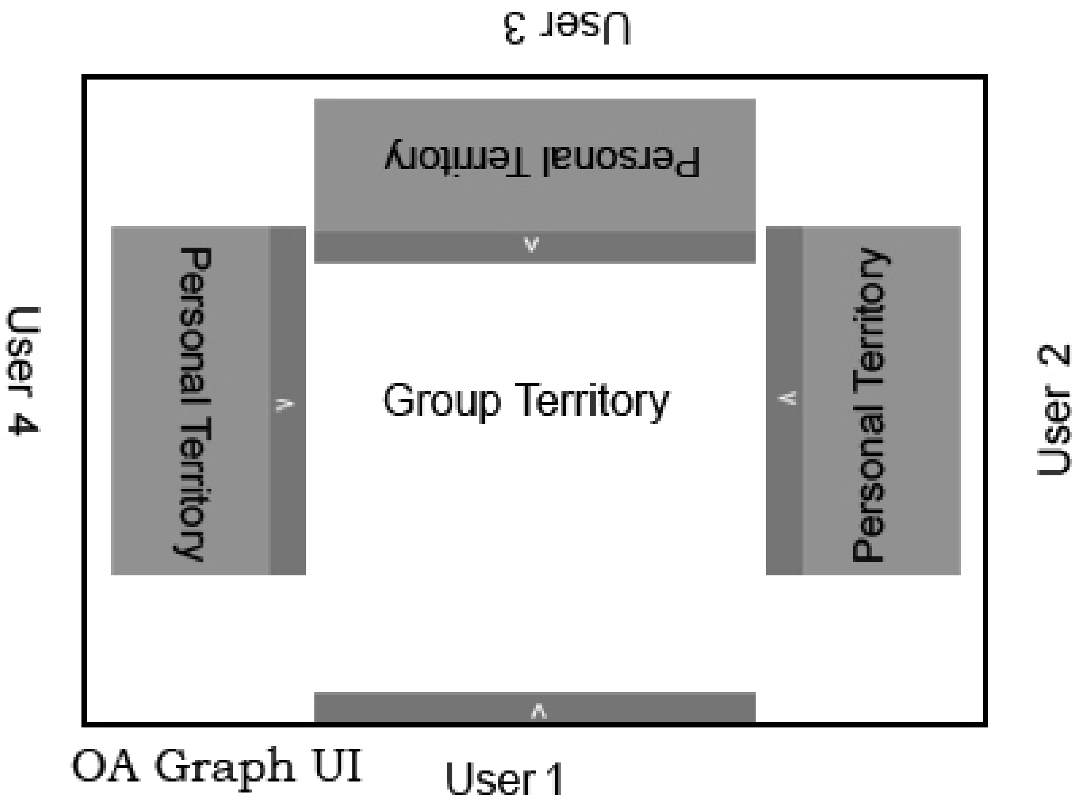
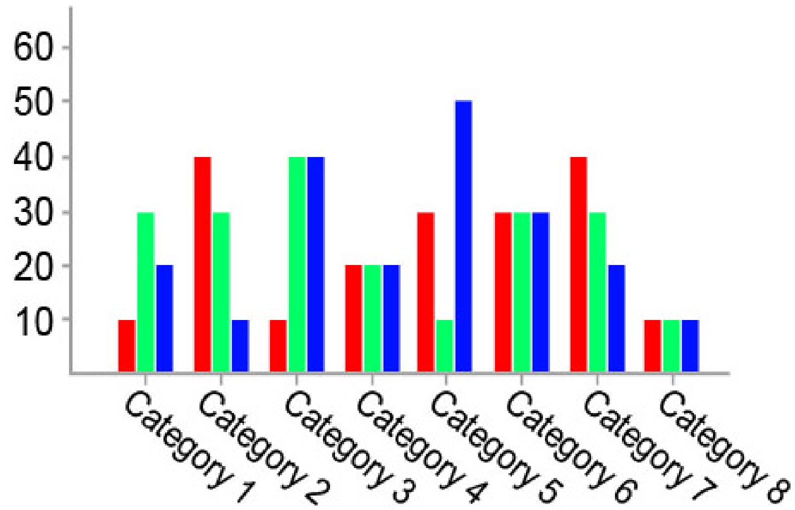


Figure 33: The design of the interface considers personal space for each user. Users can use their personal space to obtain a copy of a chart with the best view oriented toward them.

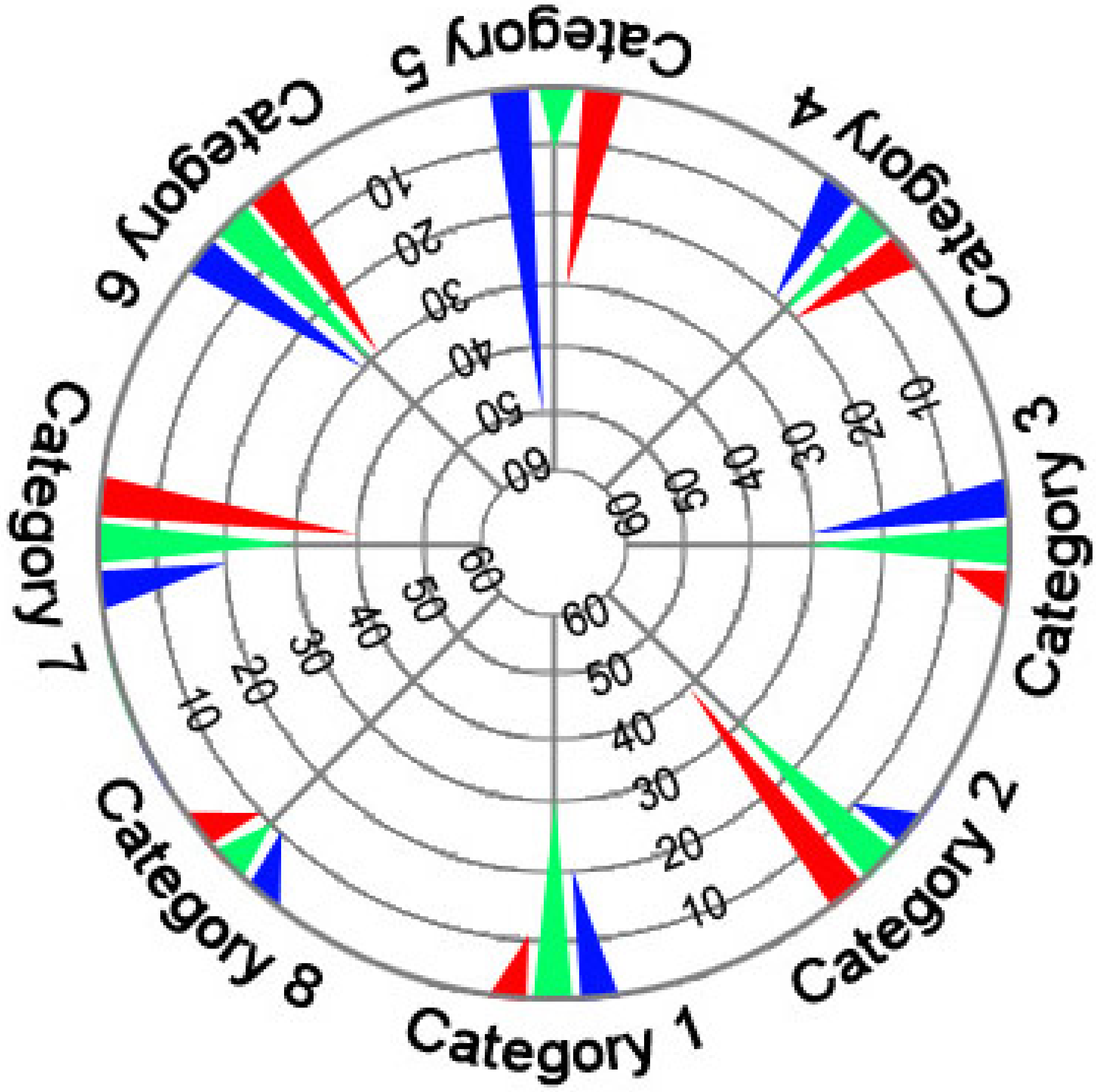
6

ORIENTATION AGNOSTIC GRAPHS CONVERSION

The study experiments have shown that OA-Graphs perform better than linear charts with an orientation angle of 180° and perform slightly worse than linear charts with an orientation angle of 0°. Providing the user with the ability to switch between different representations to support single and multiple views can be beneficial. Due to the several interesting properties of radial-based visualization, I consider transformation of commonly used and more complex charts such as bar and line charts with several datasets, parallel coordinates, and Gantt charts (see Figure 34, 35, 36 and 37).

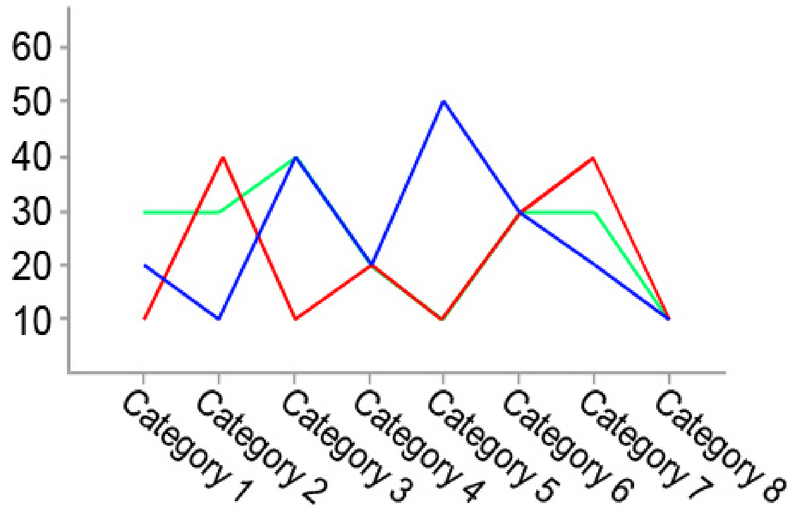


(a) Bar chart with multiple data-sets.

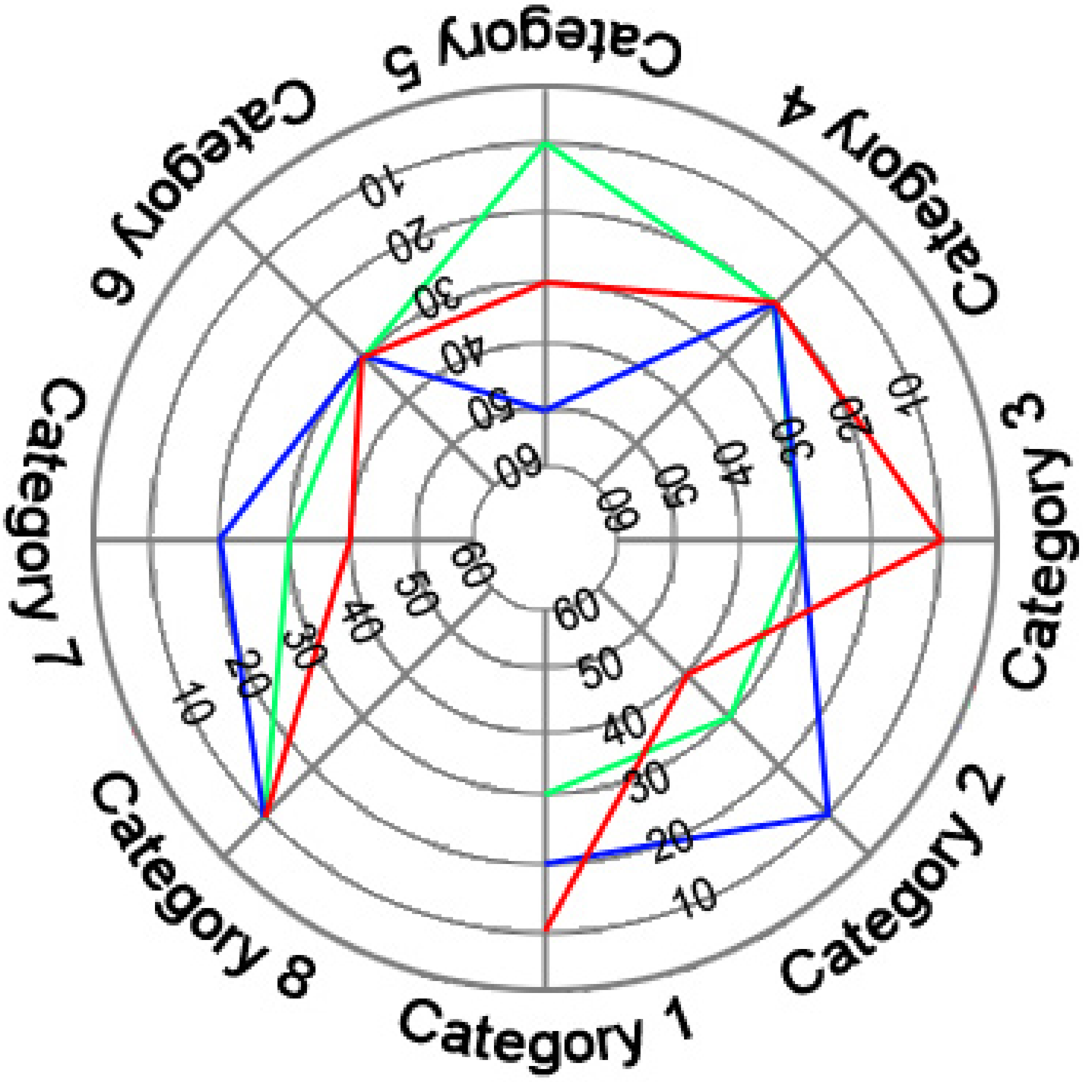


(b) Conversion to a Reference Out OA-Graph results in the creation of four repeated x-axis scales to provide easy reference for the reader.

Figure 34: The transformation of a complex bar chart into an OA-graph [4].

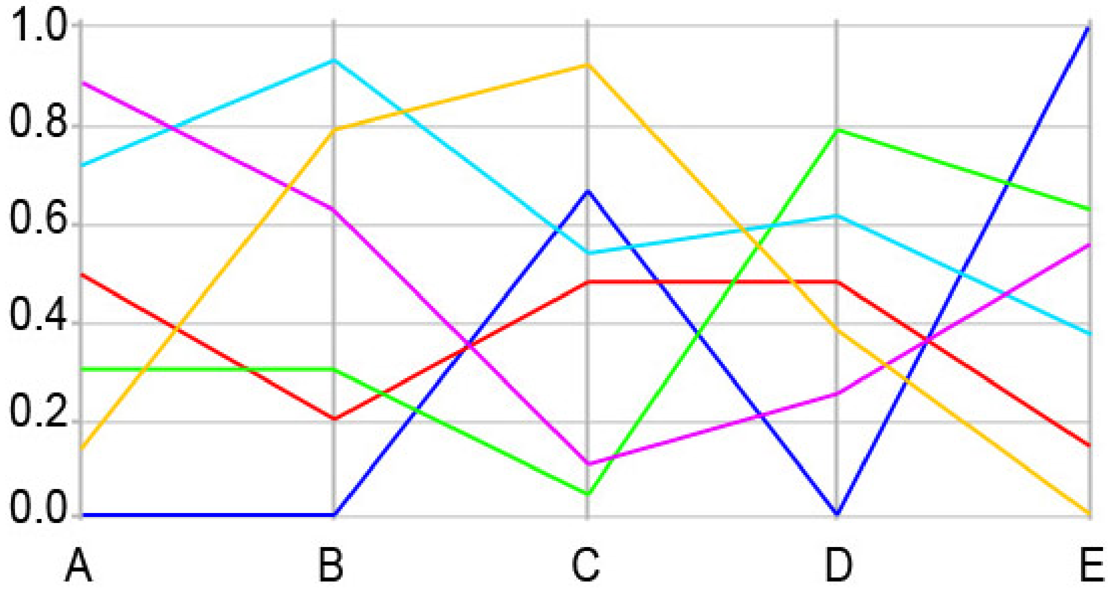


(a) Line chart with multiple data-sets.

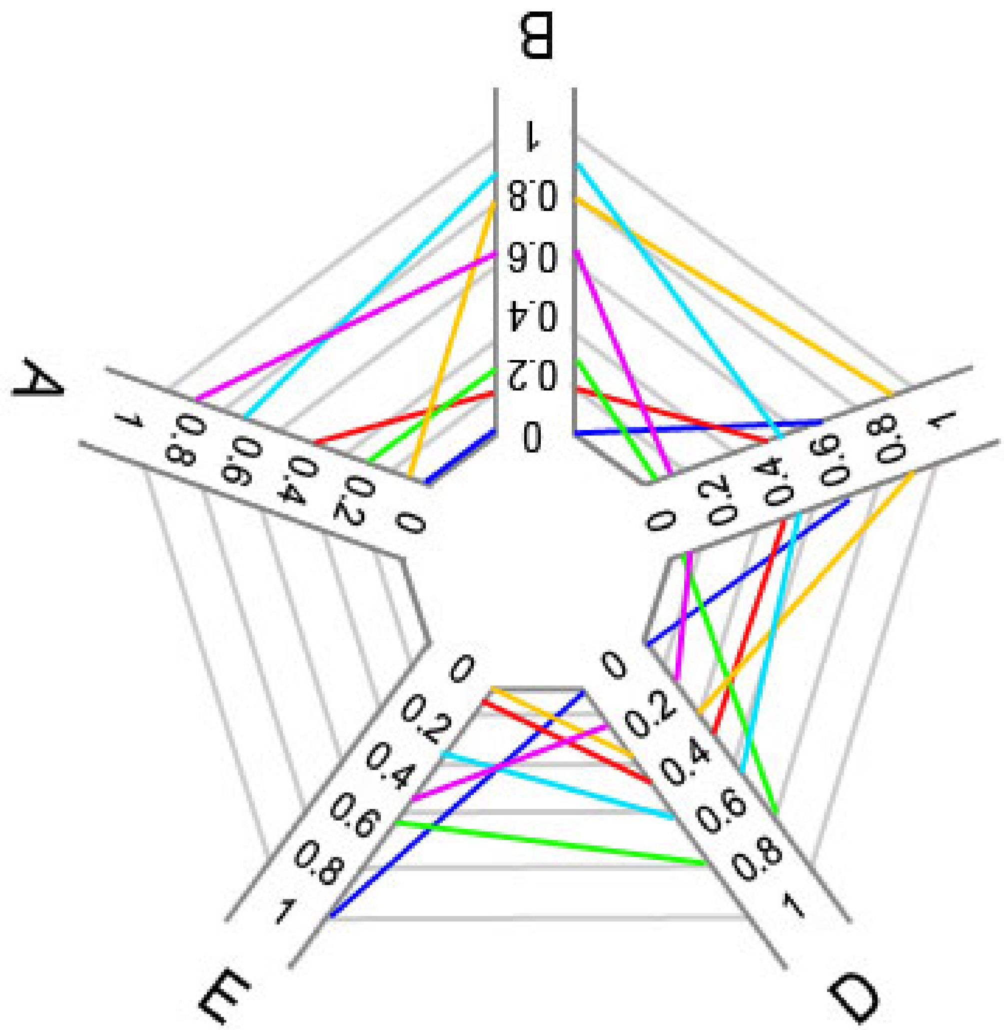


(b) The OA-Graph version of the line chart.

Figure 35: The transformation of a line chart into an OA-Graph [4].

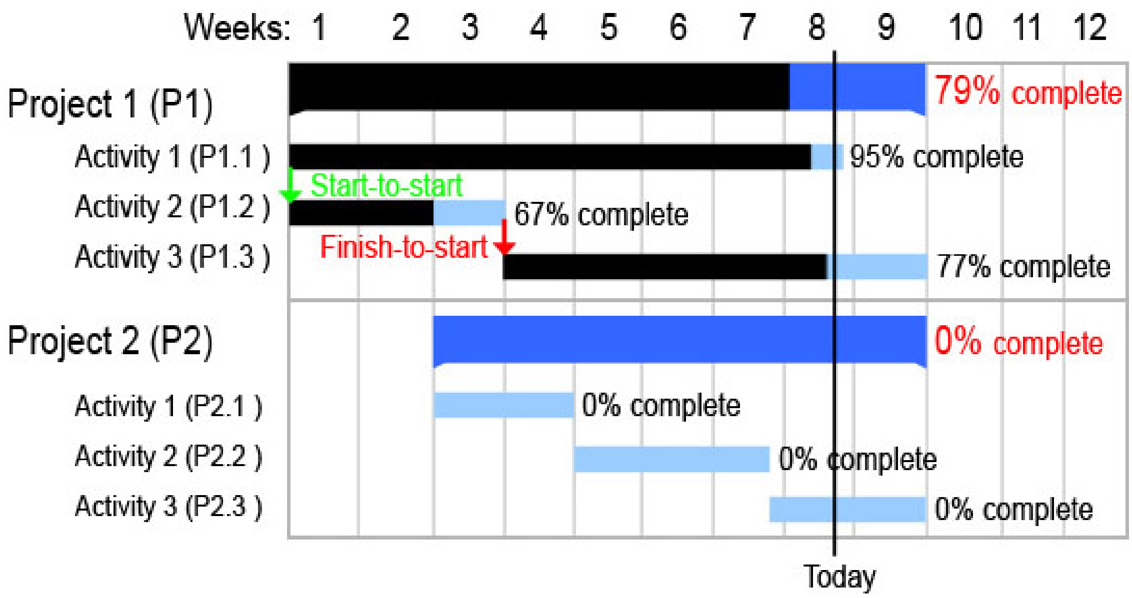


(a) A parallel coordinate graph is another visualization used to represent multivariate data.

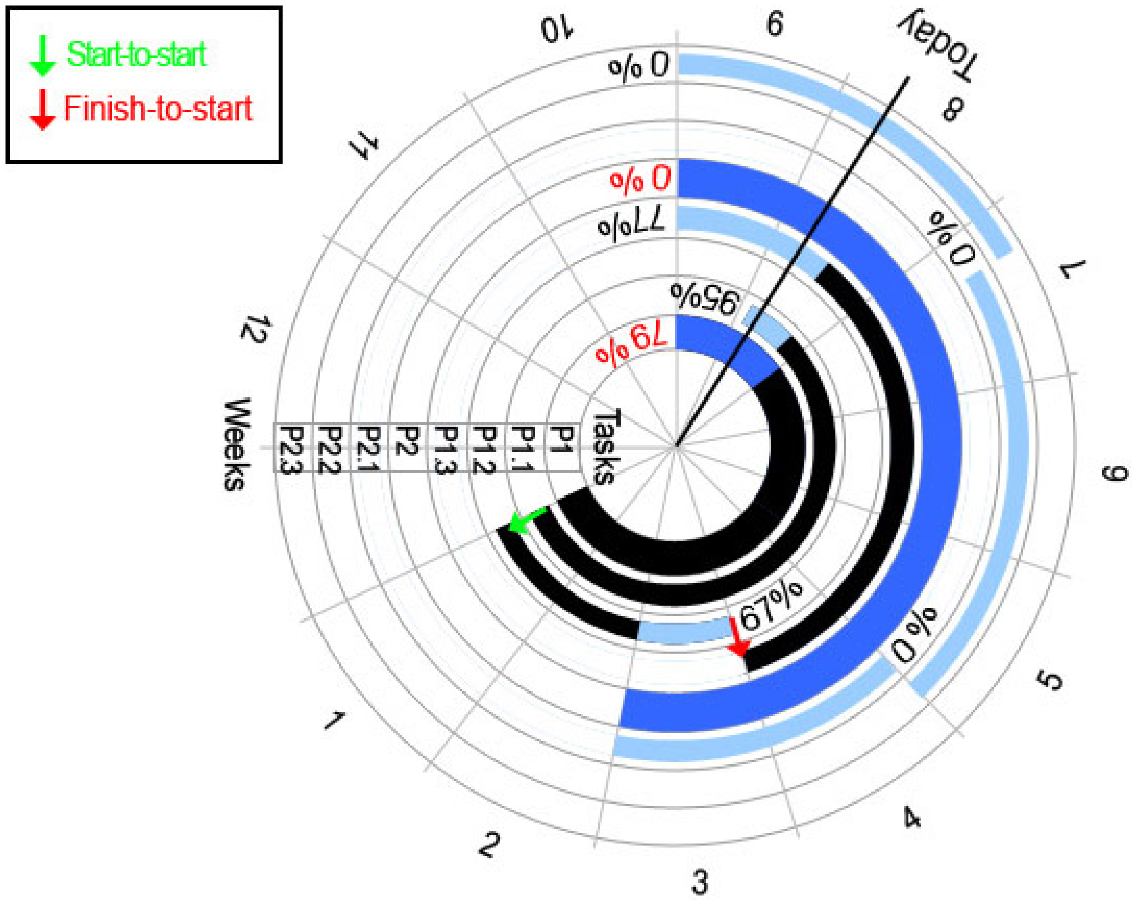


(b) Each multivariate is on a separate axis with its own scale to ease legibility. This representation can also help to compare values between the first and the last multivariate.

Figure 36: The transformation of a parallel coordinate graph into an OA-Graph [4].



(a) Gantt charts are one of the more commonly used charts in project management.



(b) Similar information of the Gantt graph is presented in an OA-Graph.

Figure 37: The transformation of a Gantt chart into an OA-Graph [4].

7

SUMMARY AND FUTURE WORK

Orientation on tabletop displays remains a critical issue that needs to be effectively addressed. This study demonstrated that a range of factors affect chart readability such as chart type, chart style, variance in pairs of points, and angle of view. It also demonstrated that the negative effects of orientation can be reduced. Tabletop interfaces should adopt different interaction scenarios when there is a need for data sharing and collaboration.

In this thesis, I studied the effect of chart orientation on tabletop surfaces as it related to chart readability using common chart types in different viewing orientations. In an attempt to address the orientation issue, I compared linear chart styles with Orientation Agnostic Graphs. My findings demonstrate that the readability of a chart can be improved using OA-Graphs in certain circumstances. OA-Graphs can be used to support multiple users with an optimal view of a chart. I have introduced a set of interaction techniques that provide a fundamental set of document manipulation mechanisms that can be used in tabletop settings to relocate, orient, and rescale document objects. In addition, I have implemented both linear and OA chart styles to allow users a choice based on their preference between a single view and multiple views for charts. I am currently investigating designs to convert some of the more common visualization techniques, such as parallel coordinates and tree visualization, so that they are Orientation Agnostic. These implementations will allow us to develop rigorous design guidelines to assist in the development of other types of orientation independent visualizations on tabletop surfaces. Additionally, I intend to evaluate existing interaction techniques used on graphs in tabletop settings to identify parameters to make these independent of orientation.

7.1 CONTRIBUTION

This study confirms and builds on previous studies that orientation in tabletop settings can have an adverse effect on perception. In this case, chart readability was negatively affected when viewed upside down. A tabletop display interface should support both ease of interaction and flexible data representation in order to reduce the effect of orientation. This is even more critical when a group of users performs a highly collaborative task such as reading a chart, where everyone is susceptible to the adverse effects of orientation on data perception. For a single user it is ideal to view a chart with an orientation angle of 0°. For a group of users, the ideal chart orientation is an Orientation Agnostic Graph (OA-Graph). One observation that I noticed during both experiments is that some users tend to move their heads to adjust the chart view for linear chart styles. It was observed that with OA charts these head movements significantly decreased. Also, during the practice session some users asked if they had a choice to do the experiment while standing, as that was their preference. This supports the study result that viewing a chart while standing helps users perform perceptual tasks faster. As a consequence, I was surprised to find that standing or sitting had no effect on the error rate.

Unlike previous work, this study assessed both visual representation issues and interaction techniques in an effort to address orientation issues with visualizations in tabletop settings. For linear chart styles I found that line and bar charts are more robust. However, bar charts turn out to be more robust than line charts when represented as OA charts. The variance of value in a chart dataset also has an effect on the completion time. Users are able to more quickly identify patterns in a chart when a range of difference in values in a chart is large.

7.2 LIMITATIONS

Orientation in tabletop settings is still a challenging issue and this can be seen in tasks that require reading text. When an individual reads a chart, he or she looks for patterns and trends and then looks for labels to refer to corresponding values. Different label placement strategies are used to facilitate orientation-independent reading in visualization interfaces. One example is to warp labels in a circular or arc fashion. Although I did not address text orientation in this study, I do see it as an important focus for future investigation in tabletop environments. The main focus of the research in this thesis was to examine the visual coding system in tabletop settings to achieve a better understanding of the effect it has on chart readability with consideration of orientation of displayed data.

7.3 FUTURE WORK

The next step in this research direction is to extend the investigation to the effects of other factors such as size of display, position and size of chart, and chart complexity that may have an effect on user perception. In addition, the OA-Graph should be examined in a groupware setting to observe the effect of aforementioned factors on both user and group perception and whether it increases group productivity. The most exciting prospect for future work in this area is the integration of OA-graph interface into visualizations of social interaction and dynamic interfaces [2, 3].

7.4 FINAL WORD

Orientation of objects in tabletop displays in general, and charts in particular, is an important issue that needs more research to explore. The more common tabletop usage becomes, the more the need for understanding proper design for its interfaces increases. The OA-Graph interface proved useful for improving user perception. I hope that techniques like the OA-Graph interface can help and contribute to improving tabletop interface designs and demonstrate an important way to improve the legibility of charts in tabletops.

BIBLIOGRAPHY

[1] Maneesh Agrawala, Andrew C. Beers, Ian McDowall, Bernd Fröhlich, Mark Bolas, and Pat Hanrahan. The two-user responsive workbench: Support for collaboration through individual views of a shared space. In *SIGGRAPH '97: Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques*, pages 327–332, New York, NY, USA, 1997. ACM Press/Addison-Wesley Publishing Co.

[2] Fouad Shoie Alallah, Mahtab Nezhadasl, Pourang Irani, and Dean Jin. Visualizing the decision-making process in a face-to-face meeting. In *IV '07: Proceedings of the 11th International Conference on Information Visualization*, pages 168–176, Washington, DC, USA, 2007. IEEE Computer Society.

[3] Fouad Shoie Alallah, Pourang Irani, and Dean Jin. Meetviz: A tool for visualizing the social interactions in a face to-face meeting. In *IV '08: Proceedings of the 12th International Conference Information Visualization Poster Session*, Columbus, Ohio, USA, 2008.

[4] Fouad Shoie Alallah, Pourang Irani, and Dean Jin. Oa-graphs: Orientation agnostic graphs for improving the legibility of charts on horizontal displays. In *ITS '10: Proceedings of the ACM International Conference on Interactive Tabletop Surfaces*, pages 211–220, Saarbrücken, Germany, November 2010. ACM Press.

[5] Robert Amar, James Eagan, and John Stasko. Low-level components of analytic activity in information visualization. In *INFOVIS '05: Proceedings of*

the 2005 IEEE Symposium on Information Visualization, page 15, Washington, DC, USA, 2005. IEEE Computer Society.

[6] Tony Bergstrom and Karrie Karahalios. Conversation votes: enabling anonymous cues. In *CHI '07: Extended Abstracts on Human Factors in Computing Systems*, pages 2279–2284, New York, NY, USA, 2007. ACM press.

[7] Jacques Bertin. *Semiology of graphics*. University of Wisconsin Press, 1983.

[8] Oscar de Bruijn and Robert Spence. Serendipity within a ubiquitous computing environment: A case for opportunistic browsing. In *UbiComp '01: Proceedings of the 3rd International Conference on Ubiquitous Computing*, pages 362–370, London, UK, 2001. Springer-Verlag.

[9] J. Chapman. Chapman-cook speed of reading test. *Ames, IA*, 1923.

[10] William. S. Cleveland and Robert. McGill. Graphical perception: Theory, experimentation, and application to the development of graphical methods. *Journal of the American Statistical Association*, 79:531–554, 1984.

[11] William. S. Cleveland and Robert. McGill. Graphical perception and graphical methods for analyzing scientific data. *Science*, 229:828–833, 1985.

[12] Lynn A. Cooper. Mental rotation of random two-dimensional shapes. *Cognitive Psychology*, 7:20–43, 1973.

[13] Lynn A. Cooper and Roger N. Shepard. Chronometric studies of the rotation of mental images. *W.G. Chase (Ed.), Visual Information Processing*, 1973.

[14] Michael Corballis, N. Zbrodoff, Larry Shetzer, and Patricia Butler. Decisions about identity and orientation of rotated letters and digits. *Memory & Cognition*, 6(2):98–107, 1978.

[15] Pierre Dragicevic and Yuanchun Shi. Visualizing and manipulating automatic document orientation methods using vector fields. In *ITS '09: Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*, pages 65–68, New York, NY, USA, 2009. ACM.

[16] Geoffrey Draper, Yarden Livnat, and Richard Riesenfeld. A survey of radial methods for information visualization. *IEEE Transactions on Visualization and Computer Graphics*, 15(5):759–776, 2009.

[17] George Fitzmaurice, Ravin Balakrishnan, Gordon Kurtenbach, and Bill Buxton. An exploration into supporting artwork orientation in the user interface. In *CHI '99: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 167–174, New York, NY, USA, 1999. ACM.

[18] Clifton Forlines, Chia Shen, Daniel Wigdor, and Ravin Balakrishnan. Exploring the effects of group size and display configuration on visual search. In *CSCW '06: Proceedings of the 2006 20th Anniversary Conference on Computer Supported Cooperative Work*, pages 11–20, New York, NY, USA, 2006. ACM.

[19] Carl Gutwin and Saul Greenberg. Design for individuals, design for groups: Tradeoffs between power and workspace awareness. In *CSCW '98: Proceedings of the 1998 ACM Conference on Computer Supported Cooperative Work*, pages 207–216, New York, NY, USA, 1998. ACM.

[20] Jefferson Han. Low-cost multi-touch sensing through frustrated total internal reflection. In *UIST '05: Proceedings of the 18th annual ACM symposium on User interface software and technology*, pages 115–118, New York, NY, USA, 2005. ACM.

[21] Mark Hancock, Sheelagh Carpendale, Frederic Vernier, Daniel Wigdor, and Chia Shen. Rotation and translation mechanisms for tabletop interaction.

In *TABLETOP '06: Proceedings of the First IEEE International Workshop on Horizontal Interactive Human-Computer Systems*, pages 79–88, Washington, DC, USA, 2006. IEEE Computer Society.

[22] Thomas Hansen, Juan Pablo Hourcade, Mathieu Virbel, Sharath Patali, and Tiago Serra. Pymt: A post-wimp multi-touch user interface toolkit. In *ITS '09: Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces*, pages 17–24, New York, NY, USA, 2009. ACM.

[23] Edmund Huey. Preliminary experiments in the physiology and psychology of reading. *The American Journal of Psychology*, 9(4):575–586, 1898.

[24] Kori Inkpen, Mark Hancock, Regan Mandryk, and Stacey Scott. Collaboration around a tabletop display: Supporting interpersonal interactions. Technical report, Simon Fraser University - EDGE Lab, 2001.

[25] Petra Isenberg and Sheelagh Carpendale. Interactive tree comparison for co-located collaborative information visualization. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1232–1239, 2007.

[26] Hiroshi Ishii, Minoru Kobayashi, and Jonathan Grudin. Integration of interpersonal space and shared workspace: Clearboard design and experiments. In *CSCW '92: Proceedings of the 1992 ACM Conference on Computer Supported Cooperative Work*, pages 33–42, New York, NY, USA, 1992. ACM.

[27] Karrie Karahalios and Tony Bergstrom. Visualizing audio in group table conversation. In *TABLETOP '06: Proceedings of the First IEEE International Workshop on Horizontal Interactive Human-Computer Systems*, pages 131–134, Washington, DC, USA, 2006. IEEE Computer Society.

[28] Paul Kolers and David Perkins. Orientation of letters and errors in their recognition. *Perception & Psychophysics*, 5(5):265–269, 1969.

[29] Asher Koriat and Joel Norman. Reading rotated words. *Journal of Experimental Psychology: Human Perception and Performance*, 11(4):490–508, 1985.

[30] Russell Kruger and Sheelagh Carpendale. The e-table: exploring collaborative interaction on a horizontal display. Technical Report 2002-714-17, University of Calgary, December 2002.

[31] Russell Kruger, Sheelagh Carpendale, Stacey Scott, and Saul Greenberg. Roles of orientation in tabletop collaboration: Comprehension, coordination and communication. *Computer Supported Cooperative Work*, 13(5-6):501–537, 2004.

[32] Russell Kruger, Sheelagh Carpendale, Stacey Scott, and Anthony Tang. Fluid integration of rotation and translation. In *CHI '05: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 601–610, New York, NY, USA, 2005. ACM.

[33] John Lamping, Ramana Rao, and Peter Pirolli. A focus+context technique based on hyperbolic geometry for visualizing large hierarchies. In *CHI '95: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 401–408, New York, NY, USA, 1995. ACM Press/Addison-Wesley Publishing Co.

[34] R. Likert. A technique for the measurement of attitudes. *Archives of Psychology*, 22(140):1–55, 1932.

[35] Matthew Luckiesh. *Light, vision and seeing : a simplified presentation of their relationships and their importance in human efficiency and welfare*. Van Nostrand, New York, 1944.

[36] Jock Mackinlay. Automating the design of graphical presentations of relational information. *ACM Transactions on Graphics*, 5(2):110–141, 1986.

[37] William Mendenhall and Terry Sincich. *Statistics for Engineering and the Sciences (5th Edition)*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 2006.

[38] Meredith Morris, Andreas Paepcke, Terry Winograd, and Jeannie Stamberger. Teamtag: exploring centralized versus replicated controls for co-located tabletop groupware. In *CHI '06: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1273–1282, New York, NY, USA, 2006. ACM.

[39] Miguel Nacenta, Satoshi Sakurai, Tokuo Yamaguchi, Yohei Miki, Yuichi Itoh, Yoshifumi Kitamura, Sriram Subramanian, and Carl Gutwin. E-conic: a perspective-aware interface for multi-display environments. In *UIST '07: Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology*, pages 279–288, New York, NY, USA, 2007. ACM.

[40] Matthias Rauterberg, Martin Bichsel, Ulf Leonhardt, and M. Meier. Build-it: a computer vision-based interaction technique of a planning tool for construction and design. In *INTERACT '97: Proceedings of the IFIP TC13 International Conference on Human-Computer Interaction*, pages 587–588, London, UK, 1997. Chapman & Hall, Ltd.

[41] Kathy Ryall, Clifton Forlines, Chia Shen, and Meredith Ringel Morris. Exploring the effects of group size and table size on interactions with tabletop shared-display groupware. In *CSCW '04: Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work*, pages 284–293, New York, NY, USA, 2004. ACM.

[42] Stacey Scott, Karen Grant, and Regan L. Mandryk. System guidelines for co-located, collaborative work on a tabletop display. In *ECSCW '03: Proceedings of the 8th European Conference on Computer Supported Cooperative Work*, pages 159–178, Norwell, MA, USA, 2003. Kluwer Academic Publishers.

[43] Chia Shen, Katherine Everitt, and Kathy Ryall. Ubitable: Impromptu face-to-face collaboration on horizontal interactive surfaces. In *Proceedings of the 5th International Conference on Ubiquitous Computing*, pages 281–288. Springer Verlag, 2003.

[44] Chia Shen, Frédéric Vernier, Clifton Forlines, and Meredith Ringel. Diamondspin: an extensible toolkit for around-the-table interaction. In *CHI '04: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 167–174, New York, NY, USA, 2004. ACM.

[45] Chia Shen, Kathy Ryall, Clifton Forlines, Alan Esenther, Frederic Vernier, Katherine Everitt, Mike Wu, Daniel Wigdor, Meredith Ringel Morris, Mark Hancock, and Edward Tse. Informing the design of direct-touch tabletops. *IEEE Computer Graphics and Applications*, 26(5):36–46, 2006.

[46] Roger Shepard and Jacqueline Metzler. Mental rotation of three-dimensional objects. *Science*, 171(3972):701–703, February 1971.

[47] Robert Spence. *Information Visualization: Design for Interaction (2nd Edition)*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 2nd edition edition, 2007.

[48] John Stasko and Eugene Zhang. Focus+context display and navigation techniques for enhancing radial, space-filling hierarchy visualizations. In *INFOVIS '00: Proceedings of the IEEE Symposium on Information Vizualization 2000*, page 57, Washington, DC, USA, 2000. IEEE Computer Society.

[49] Norbert Streitz, Jörg Gei, Torsten Holmer, Shin'ichi Konomi, Christian Müller-Tomfelde, Wolfgang Reischl, Petra Rexroth, Peter Seitz, and Ralf Steinmetz. i-land: an interactive landscape for creativity and innovation. In *CHI '99: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 120–127, New York, NY, USA, 1999. ACM.

[50] Norbert Streitz, Peter Tandler, Christian Müller-Tomfelde, and S. Konomi. Roomware: Towards the next generation of human-computer interaction based on an integrated design of real and virtual worlds. In *Human-Computer Interaction in the New Millennium*, pages 553–578. Addison-Wesley, 2001.

[51] Janienke Sturm, Olga Houben-van Herwijnen, Anke Eyck, and Jacques Terken. Influencing social dynamics in meetings through a peripheral display. In *ICMI '07: Proceedings of the 9th International Conference on Multimodal Interfaces*, pages 263–270, New York, NY, USA, 2007. ACM.

[52] Ahmed Sulaiman and Patrick Olivier. Attribute gates. In *UIST '08: Proceedings of the 21st Annual ACM Symposium on User Interface Software and Technology*, pages 57–66, New York, NY, USA, 2008. ACM.

[53] Peter Tandler, Thorsten Prante, Christian Müller-Tomfelde, Norbert Streitz, and Ralf Steinmetz. Connectables: dynamic coupling of displays for the flexible creation of shared workspaces. In *UIST '01: Proceedings of the 14th Annual ACM Symposium on User Interface Software and Technology*, pages 11–20, New York, NY, USA, 2001. ACM.

[54] John Tang. *Listing, Drawing, and Gesturing in Design: A Study of the Use of Shared Workspaces by Design Teams*. Ph.d. thesis, Stanford University, Department of Mechanical Engineering, April 1989. Xerox PARC Technical Report SSL-89-3.

[55] John Tang. *Findings from Observational Studies of Collaborative Work*, pages 11–28. Academic Press Ltd., London, UK, 1991.

[56] Richard Taylor. Reading spatially transformed digits. *Journal of Experimental Psychology*, 96(2):296–399, 1969.

[57] Miles Tinker. Effects of angular alignment upon readability of print. *Journal of Educational Psychology*, 47(6):358–363, 1972.

[58] Matthew Tobiasz, Petra Isenberg, and Sheelagh Carpendale. Lark: Coordinating co-located collaboration with information visualization. *IEEE Transactions on Visualization and Computer Graphics*, 15(6):1065–1072, 2009.

[59] Frédéric Vernier, Neal Lesh, and Chia Shen. Visualization techniques for circular tabletop interfaces. In *AVI '02: Proceedings of the Working Conference on Advanced Visual Interfaces*, pages 257–265, New York, NY, USA, 2002. ACM.

[60] Pierre Wellner. Interacting with paper on the digitaldesk. *Communications of the ACM*, 36(7):87–96, 1993.

[61] Daniel Wigdor and Ravin Balakrishnan. Empirical investigation into the effect of orientation on text readability in tabletop displays. In *ECSCW '05: Proceedings of the 9th conference on European Conference on Computer Supported Cooperative Work*, pages 205–224, New York, NY, USA, 2005. Springer-Verlag New York, Inc.

[62] Daniel Wigdor, Chia Shen, Clifton Forlines, and Ravin Balakrishnan. Perception of elementary graphical elements in tabletop and multi-surface environments. In *CHI '07: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 473–482, New York, NY, USA, 2007. ACM.

[63] J. Zhang and A. D. Norman. Representations in distributed cognitive tasks. *Cognitive Science*, 18:87–122, 1994.

A

MATERIAL FROM EXPERIMENTS

A.1 EXPERIMENT1

Univariate Analysis of Variance (completion time)

Between-Subjects Factors

		Value Label	N
Orientation	Down	0 degree	795
	Left	270 degree	766
	Right	90 degree	751
	Up	180 degree	732
GraphType	Area		670
	Bar		790
	Line		814
	Scatter		770
DifferncelnValue	4		968
	6		999
	10		1077

Tests of Between-Subjects Effects

Dependent Variable:Time_inMilli

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.650E10	47	3.511E8	13.942	.000
Intercept	4.043E11	1	4.043E11	16053.557	.000
Orientation	3.271E9	3	1.090E9	68.401	.000
GraphType	2.649E8	3	8.831E7	20.352	.001
DifferncelnValue	8.266E9	2	4.133E9	301.359	.000
Orientation * GraphType	6.624E8	9	7.360E7	4.294	.001
Orientation * DifferncelnValue	7.956E8	6	1.326E8	3.976	.000
GraphType * DifferncelnValue	1.083E9	6	1.805E8	18.570	.000
Error	7.545E10	2996	2.518E7		
Total	5.046E11	3044			
Corrected Total	9.195E10	3043			

a. R Squared = .179 (Adjusted R Squared = .167)

Estimated Marginal Means

1. Grand Mean

Dependent Variable:Time_inMilli

Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
11753.151	92.762	11571.268	11935.034

2. Orientation

Estimates

Dependent Variable:Time_inMilli

Orientation	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0 degree	9975.424	180.973	9631.580	10319.267
270 degree	12357.374	185.458	12100.486	12614.261
90 degree	12242.368	185.638	11740.158	12744.958
180 degree	12181.087	189.917	11817.205	12544.969

Pairwise Comparisons

Dependent Variable:Time_inMilli

(I) Orientation	(J) Orientation	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	95% Confidence Interval for Difference[a] Upper Bound
0 degree	270 degree	-2381.950*	259.125	.000	-3114.993	-1648.907
	90 degree	-2267.134*	259.254	.000	-3100.977	-1433.292
	180 degree	-2205.663*	262.335	.000	-2900.731	-1510.595
270 degree	0 degree	2381.950*	259.125	.000	1846.107	2917.793
	90 degree	114.816	262.404	1.000	-579.094	808.725
	180 degree	176.287	265.449	1.000	-378.751	731.326
90 degree	0 degree	2267.134*	259.254	.000	1732.112	2802.157
	270 degree	-114.816	262.404	1.000	-806.405	576.774
	180 degree	61.471	265.575	1.000	-492.739	615.682
180 degree	0 degree	2205.663*	262.335	.000	1515.595	2895.731
	270 degree	-176.287	265.449	1.000	-1022.826	670.251
	90 degree	-61.471	265.575	1.000	-909.502	786.559

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Time_inMilli

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	3.271E9	3	1.090E9	68.401	.000
Error	7.545E10	2996	2.518E7		

The F tests the effect of Orientation. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

3. GraphType

Estimates

Dependent Variable:Time_inMilli

Graph Type	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Area	11486.126	200.875	11254.958	11717.293
Bar	11523.480	179.688	11021.155	12025.804
Line	11024.515	178.173	9898.707	12150.324
Scatter	12811.328	182.459	11831.571	13791.085

Pairwise Comparisons

Dependent Variable:Time_inMilli

(I) Graph Type	(J) Graph Type	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Area	Bar	-37.354	269.516	1.000	-436.178	361.471
	Line	461.611	268.508	.004	-861.008	1784.229
	Scatter	-1325.202	271.371	.054	1256.924	-3907.329
Bar	Area	37.354	269.516	1.000	-361.471	436.178
	Line	498.964	253.049	.548	-1095.541	2093.469
	Scatter	-1287.848*	256.084	.009	-2715.481	139.784
Line	Area	-461.611	268.508	.004	-1784.229	861.008
	Bar	-498.964	253.049	.548	-2093.469	1095.541
	Scatter	-1786.813	255.023	.006	-3858.531	284.906
Scatter	Area	1325.202	271.371	.054	3907.329	-1256.924
	Bar	1287.848*	256.084	.009	-139.784	2715.481
	Line	1786.813	255.023	.006	-284.906	3858.531

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

*. The mean difference is significant at the .05 level.

Univariate Tests

Dependent Variable:Time_inMilli

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	2.649E8	3	8.831E7	20.352	.001
Error	7.545E10	2996	2.518E7		

The F tests the effect of GraphType. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

4. DifferncelnValue

Estimates

Dependent Variable:Time_inMilli

DifferncelnVal...	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
4	14162.513	162.407	13536.072	14788.954
6	11361.153	162.992	11315.566	11406.740
10	10065.786	156.525	9462.878	10668.694

Pairwise Comparisons

Dependent Variable:Time_inMilli

(I) DifferncelnValue	(J) DifferncelnValue	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
4	6	2219.360*	230.092	.000	1668.215	5096.213
	10	4084.727*	225.558	.000	3544.443	4696.076
6	4	-2219.360*	230.092	.000	-5096.213	-1668.215
	10	1865.367*	225.979	.000	1324.073	152.018
10	4	-4084.727*	225.558	.000	-4696.076	-3544.443
	6	-1865.367*	225.979	.000	-152.018	-1324.073

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Time_inMilli

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	8.266E9	2	4.133E9	19.288	.000
Error	7.545E10	2996	2.518E7		

The F tests the effect of DiffernceInValue. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

5. Orientation * GraphType

Dependent Variable:Time_inMilli

Orientation	Graph Type	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
0 degree	Area	9324.385	383.714	8572.016	10076.448
	Bar	9508.918	360.663	8801.746	10216.090
	Line	9966.981	339.168	9301.955	10031.846
	Scatter	11057.410	362.863	10345.925	13558.145
270 degree	Area	11541.725	419.963	10718.280	11830.940
	Bar	12268.497	350.270	11581.703	12995.291
	Line	13087.339	351.227	10300.669	12097.952
	Scatter	13080.934	357.625	12379.719	13760.881

5. Orientation * GraphType

Dependent Variable:Time_inMilli

Orientation	Graph Type	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
90 degree	Area	13057.389	362.252	12347.101	13744.039
	Bar	12166.109	373.584	11433.601	13898.617
	Line	11686.306	383.291	10934.766	12597.656
	Scatter	12614.068	365.619	11897.179	15884.978
180 degree	Area	12671.804	436.787	11815.370	12784.812
	Bar	11550.393	352.524	10859.180	12401.607
	Line	12463.250	350.178	10776.636	12154.645
	Scatter	12004.900	373.386	11272.782	13391.018

6. Orientation * DifferncelnValue

Dependent Variable:Time_inMilli

Orientation	Differnce In Value	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
0 degree	4	11463.254	319.609	10584.580	12341.929
	6	9421.907	295.412	9138.065	9705.748
	10	8967.720	324.565	8328.328	9607.113
270 degree	4	15425.127	329.514	14479.031	16371.224
	6	12019.123	336.976	11659.649	12378.597
	10	10209.367	295.668	9458.635	10960.099
90 degree	4	14772.890	326.670	13638.370	15907.411
	6	12577.480	341.283	12207.758	12947.202
	10	9997.084	294.897	9408.863	10585.306
180 degree	4	14988.779	323.380	14168.709	15808.850
	6	11426.101	328.277	10982.336	11869.867
	10	11088.973	335.078	9431.968	12745.979

7. GraphType * DifferncelnValue

Dependent Variable:Time_inMilli

Graph Type	Differnce In Value	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Area	4	14638.136	330.405	13990.597	15285.674
	6	11002.072	363.542	10310.255	11693.890
	10	9374.965	349.039	8600.584	10149.346
Bar	4	13826.427	329.434	12181.185	15471.670
	6	9730.781	307.933	9526.998	9934.563
	10	9962.533	295.365	9283.394	10641.672
Line	4	13345.463	305.749	12765.961	13924.964
	6	11910.289	329.361	10039.492	13781.086
	10	9736.158	289.397	8784.721	10687.594
Scatter	4	14840.026	332.927	13934.237	15745.814

7. GraphType * DifferncelnValue

Dependent Variable:Time_inMilli

Graph Type	Differnce In Value	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Scatter	6	12801.469	299.327	11814.562	13788.376
	10	11189.489	314.934	9961.980	12416.999

Post Hoc Tests

Orientation

Multiple Comparisons

Dependent Variable:Time_inMilli

	(I) Orientation	(J) Orientation	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	0 degree	270 degree	-2381.95*	254.074	.000	-3114.99	-1648.91
		90 degree	-2267.13*	255.363	.000	-3100.98	-1433.29
		180 degree	-2205.66*	257.062	.000	-2900.73	-1510.60
	270 degree	0 degree	2381.95*	254.074	.000	1846.11	2917.79
		90 degree	114.82	257.701	1.000	-579.09	808.73
		180 degree	176.29	259.384	1.000	-378.75	731.33
	90 degree	0 degree	2267.13*	255.363	.000	1732.11	2802.16
		270 degree	-114.82	257.701	1.000	-806.41	576.77
		180 degree	61.47	260.647	1.000	-492.74	615.68
	180 degree	0 degree	2205.66*	257.062	.000	1515.60	2895.73
		270 degree	-176.29	259.384	1.000	-1022.83	670.25
		90 degree	-61.47	260.647	1.000	-909.50	786.56
Tamhane	0 degree	270 degree	-2381.95*	276.685	.000	-3114.99	-1648.91
		90 degree	-2267.13*	261.314	.000	-3100.93	-1433.31
		180 degree	-2205.66*	254.527	.000	-2900.72	-1510.61
	270 degree	0 degree	2381.95*	276.685	.000	1846.01	2917.34
		90 degree	114.82	298.919	1.000	-579.01	808.11
		180 degree	176.29	293.004	.977	-378.60	731.18
	90 degree	0 degree	2267.13*	261.314	.000	1732.10	2802.03
		270 degree	-114.82	298.919	1.000	-806.21	576.57
		180 degree	61.47	278.535	.999	-492.74	615.68
	180 degree	0 degree	2205.66*	254.527	.000	1515.54	2895.15
		270 degree	-176.29	293.004	.977	-1022.83	670.25
		90 degree	-61.47	278.535	.999	-909.50	786.56

Based on observed means.
The error term is Mean Square(Error) = 25183393.034.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

GraphType

Multiple Comparisons

Dependent Variable:Time_inMilli

	(I) Graph Type	(J) Graph Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Bonferroni	Area	Bar	-37.35	263.562	1.000	-436.18	361.47
		Line	461.61	261.773	.004	-861.01	1784.23
		Scatter	-1325.20	265.128	.054	-1256.92	-3907.33
	Bar	Area	37.35	263.562	1.000	-361.47	436.18
		Line	498.96	250.630	.548	-1095.54	2093.47
		Scatter	-1287.85*	254.133	.009	-2715.48	139.78
	Line	Area	-461.61	261.773	.004	-1784.23	861.01
		Bar	-498.96	250.630	.548	-2093.47	1095.54
		Scatter	-1786.81	252.277	.006	-3858.53	284.91
	Scatter	Area	1325.20	265.128	.054	-3907.33	-1256.92
		Bar	1287.85*	254.133	.009	-139.78	2715.48
		Line	1786.81	252.277	.006	-284.91	3858.53
Tamhane	Area	Bar	-37.35	288.166	.988	-436.21	361.47
		Line	461.61	286.538	.004	-861.06	1784.23
		Scatter	-1325.20	296.214	.051	-1255.55	-3907.33
	Bar	Area	37.35	288.166	.968	-361.47	436.18
		Line	498.96	268.654	.558	-1095.57	2093.47
		Scatter	-1287.85*	278.952	.007	-2715.48	139.78
	Line	Area	-461.61	286.538	.004	-1784.23	861.01
		Bar	-498.96	268.654	.505	-2058.86	1095.54
		Scatter	-1786.81	277.269	.006	-3858.53	284.91
	Scatter	Area	1325.20	296.214	.054	-3907.33	-1256.92
		Bar	1287.85*	278.952	.007	-139.78	2715.48
		Line	1786.81	277.269	.006	-284.91	3858.53

Based on observed means.
The error term is Mean Square(Error) = 25183393.034.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

DiffernceInValue

Multiple Comparisons

Dependent Variable:Time_inMilli

	(I) DifferenceInValue	(J) DifferenceInValue	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	4	6	3382.21*	226.328	.000	1668.21	5096.21
		10	4120.26*	222.258	.000	3544.44	4696.08
	6	4	-3382.21*	226.328	.000	-5096.21	-1668.21
		10	738.05*	220.435	.000	1324.07	152.02
	10	4	-4120.26*	222.258	.000	-4696.08	-3544.44
		6	-738.05*	220.435	.000	-152.02	-1324.07
Tamhane	4	6	3382.21*	257.922	.000	1552.27	5096.21
		10	4120.26*	234.137	.000	3445.73	4696.08
	6	4	-3382.21*	257.922	.000	-2785.05	-1668.21
		10	738.05*	213.978	.000	1325.30	152.02
	10	4	-4120.26*	234.137	.000	-4564.93	-3544.44
		6	-738.05*	213.978	.000	-2348.04	-1324.07

Based on observed means.
The error term is Mean Square(Error) = 25183393.034.

*. The mean difference is significant at the .05 level.

Univariate Analysis of Variance (error rate)

Between-Subjects Factors

		Value Label	N
Orientation	Down	0 degree	938
	Left	270 degree	940
	Right	90 degree	940
	Up	180 degree	938
GraphType	Area		944
	Bar		940
	Line		943
	Scatter		929
DifferncelnValue	4		1236
	6		1255
	10		1265

Tests of Between-Subjects Effects

Dependent Variable:Error

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	74.133[a]	47	1.577	11.630	.000
Intercept	135.156	1	135.156	996.538	.000
Orientation	2.188	3	.729	5.550	.001
GraphType	13.351	3	4.450	36.096	.000
DifferncelnValue	3.249	2	1.624	19.288	.000
Orientation * GraphType	12.459	9	1.384	13.772	.000
Orientation * DifferncelnValue	10.257	6	1.709	21.805	.000
GraphType * DifferncelnValue	11.292	6	1.882	13.877	.000
Error	502.898	3708	.136		
Total	712.000	3756			
Corrected Total	577.031	3755			

a. R Squared = .128 (Adjusted R Squared = .117)

Estimated Marginal Means

1. Grand Mean

Dependent Variable:Error

Mean	Std. Error	95% Confidence Interval	
		Lower Bound	Upper Bound
.190	.006	.178	.202

2. Orientation

Estimates

Dependent Variable:Error

Orientation	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
0 degree	.153	.012	.129	.177
270 degree	.185	.012	.162	.209
90 degree	.202	.012	.178	.225
180 degree	.220	.012	.195	.245

Pairwise Comparisons

Dependent Variable:Error

(I) Orientation	(J) Orientation	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
0 degree	270 degree	-.033	.017	.574	-.078	.013
	90 degree	-.049*	.017	.040	-.094	-.004
	180 degree	-.067*	.017	.002	-.110	-.024
270 degree	0 degree	.033	.017	.574	-.013	.078
	90 degree	-.016	.017	1.000	-.061	.029
	180 degree	-.035	.017	.336	-.077	.012
90 degree	0 degree	.049*	.017	.040	.004	.094
	270 degree	.016	.017	1.000	-.029	.061
	180 degree	-.018	.017	1.000	-.061	.028
180 degree	0 degree	.067*	.017	.002	.024	.110
	270 degree	.035	.017	.336	-.012	.077
	90 degree	.018	.017	1.000	-.028	.061

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

*. The mean difference is significant at the .05 level.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	2.188	3	.729	5.550	.001
Error	502.898	3708	.136		

The F tests the effect of Orientation. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

3. GraphType

Estimates

Dependent Variable:Error

Graph Type	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Area	.290	.012	.267	.314
Bar	.160	.012	.136	.183
Line	.135	.012	.113	.157
Scatter	.172	.012	.148	.196

Pairwise Comparisons

Dependent Variable:Error

(I) Graph Type	(J) Graph Type	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Area	Bar	.131*	.017	.000	.086	.176
	Line	.155*	.017	.000	.109	.198
	Scatter	.118*	.017	.000	.074	.163
Bar	Area	-.131*	.017	.000	-.176	-.086
	Line	.024	.017	1.000	-.022	.068
	Scatter	-.012	.017	1.000	-.057	.033
Line	Area	-.155*	.017	.000	-.198	-.109
	Bar	-.024	.017	1.000	-.068	.022
	Scatter	-.037	.017	.236	-.080	.010
Scatter	Area	-.118*	.017	.000	-.163	-.074
	Bar	.012	.017	1.000	-.033	.057
	Line	.037	.017	.236	-.010	.080

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	13.351	3	4.450	36.096	.000
Error	502.898	3708	.136		

The F tests the effect of GraphType. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

4. DiffernceInValue

Estimates

Dependent Variable:Error

DifferncelnVal...	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
4	.217	.010	.197	.238
6	.203	.010	.183	.224
10	.149	.010	.129	.169

Pairwise Comparisons

Dependent Variable:Error

(I) DifferncelnValue	(J) DifferncelnValue	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	95% Confidence Interval for Difference[a] Upper Bound
4	6	.014	.015	1.000	-.021	.049
	10	.068*	.015	.000	.033	.103
6	4	-.014	.015	1.000	-.049	.021
	10	.054*	.015	.002	.019	.089
10	4	-.068*	.015	.000	-.103	-.033
	6	-.054*	.015	.002	-.089	-.019

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

*. The mean difference is significant at the .05 level.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	3.249	2	1.624	19.288	.000
Error	502.898	3708	.136		

The F tests the effect of DifferncelnValue. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

5. Orientation * GraphType

Dependent Variable:Error

Orientation	Graph Type	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0 degree	Area	.217	.024	.170	.264
	Bar	.164	.024	.117	.211
	Line	.076	.024	.029	.123
	Scatter	.154	.024	.106	.202
270 degree	Area	.337	.024	.290	.384
	Bar	.128	.024	.081	.175
	Line	.123	.024	.077	.168
	Scatter	.154	.024	.107	.201
90 degree	Area	.173	.024	.125	.220

5. Orientation * GraphType

Dependent Variable:Error

Orientation	Graph Type	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
90 degree	Bar	.227	.024	.180	.274
	Line	.224	.024	.177	.271
	Scatter	.184	.024	.137	.231
180 degree	Area	.435	.024	.388	.481
	Bar	.120	.024	.073	.167
	Line	.123	.024	.076	.170
	Scatter	.196	.024	.148	.243

6. Orientation * DifferncelnValue

Dependent Variable:Error

Orientation	Differ nceIn Val...	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
0 degree	4	.188	.021	.147	.229
	6	.082	.021	.042	.123
	10	.188	.021	.148	.229
270 degree	4	.232	.021	.191	.273
	6	.237	.021	.196	.278
	10	.089	.021	.048	.129
90 degree	4	.230	.021	.189	.271
	6	.287	.021	.246	.328
	10	.088	.021	.048	.128
180 degree	4	.219	.021	.178	.260
	6	.206	.021	.165	.247
	10	.231	.021	.190	.271

7. GraphType * DifferncelnValue

Dependent Variable:Error

Graph Type	Differ nceIn Val...	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Area	4	.239	.021	.198	.280
	6	.341	.021	.301	.382
	10	.291	.021	.250	.331
Bar	4	.253	.021	.212	.294
	6	.144	.021	.103	.185
	10	.082	.021	.041	.123
Line	4	.132	.021	.091	.173
	6	.228	.021	.187	.269
	10	.051	.021	.010	.091
Scatter	4	.244	.021	.203	.286
	6	.099	.021	.058	.140
	10	.173	.021	.132	.214

Post Hoc Tests

Orientation

Multiple Comparisons

Dependent Variable:Error

	(I) Orientation	(J) Orientation	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	0 degree	270 degree	-.0325	.01700	.574	-.0775	.0122
		90 degree	-.0488*	.01700	.040	-.0935	-.0037
		180 degree	-.0670*	.01701	.002	-.1121	-.0223
	270 degree	0 degree	.0325	.01700	.574	-.0122	.0775
		90 degree	-.0163	.01699	1.000	-.0608	.0289
		180 degree	-.0345	.01700	.336	-.0794	.0104
	90 degree	0 degree	.0488*	.01700	.040	.0037	.0935
		270 degree	.0163	.01699	1.000	-.0289	.0608
		180 degree	-.0182	.01700	1.000	-.0634	.0263
	180 degree	0 degree	.0670*	.01701	.002	.0223	.1121
		270 degree	.0345	.01700	.336	-.0104	.0794
		90 degree	.0182	.01700	1.000	-.0263	.0634
Tamhane	0 degree	270 degree	-.0327	.01728	.573	-.0782	.0129
		90 degree	-.0486*	.01758	.040	-.0949	-.0023
		180 degree	-.0672*	.01791	.003	-.1143	-.0200
	270 degree	0 degree	.0327	.01728	.573	-.0129	.0782
		90 degree	-.0160	.01821	.950	-.0639	.0320
		180 degree	-.0345	.01854	.336	-.0833	.0143
	90 degree	0 degree	.0486*	.01758	.040	.0023	.0949
		270 degree	.0160	.01821	.950	-.0320	.0639
		180 degree	-.0186	.01881	.979	-.0681	.0310
	180 degree	0 degree	.0672*	.01791	.003	.0200	.1143
		270 degree	.0345	.01854	.336	-.0143	.0833
		90 degree	.0186	.01881	.979	-.0310	.0681

Based on observed means.
The error term is Mean Square(Error) = .136.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

GraphType

Multiple Comparisons

Dependent Variable:Error

	(I) Graph Type	(J) Graph Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	Area	Bar	.1307*	.01697	.000	.0859	.1755
		Line	.1551*	.01696	.000	.1087	.1982
		Scatter	.1185*	.01702	.000	.0742	.1640
	Bar	Area	-.1308*	.01697	.000	-.1755	-.0859
		Line	.0243	.01697	1.000	-.0220	.0676
		Scatter	-.0123	.01704	1.000	-.0566	.0334
	Line	Area	-.1551*	.01696	.000	-.1982	-.1087
		Bar	-.0243	.01697	1.000	-.0676	.0220
		Scatter	-.0366	.01702	.236	-.0793	.0106
	Scatter	Area	-.1185*	.01702	.000	-.1640	-.0742
		Bar	.0123	.01704	1.000	-.0334	.0566
		Line	.0366	.01702	.236	-.0106	.0793
Tamhane	Area	Bar	.1307*	.01901	.000	.0806	.1807
		Line	.1540*	.01854	.000	.1046	.2023
		Scatter	.1186*	.01927	.000	.0683	.1699
	Bar	Area	-.1307*	.01901	.000	-.1807	-.0806
		Line	.0243	.01638	.960	-.0204	.0659
		Scatter	-.0123	.01720	.985	-.0569	.0337
	Line	Area	-.1551*	.01854	.000	-.2023	-.1046
		Bar	-.0243	.01638	.960	-.0659	.0204
		Scatter	-.0366	.01668	.215	-.0783	.0096
	Scatter	Area	-.1185*	.01927	.000	-.1699	-.0683
		Bar	.0123	.01720	.985	-.0337	.0569
		Line	.0366	.01668	.215	-.0096	.0783

Based on observed means.
The error term is Mean Square(Error) = .136.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

DiffernceInValue

Multiple Comparisons

Dependent Variable:Error

	(I) DifferenceInValue	(J) DifferenceInValue	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Bonferroni	4	6	.0140	.01476	1.000	-.0225	.0482
		10	.0681*	.01473	.000	.0329	.1035
	6	4	-.0140	.01476	1.000	-.0482	.0225
		10	.0541*	.01467	.000	.0202	.0905
	10	4	-.0681*	.01473	.000	-.1035	-.0329
		6	-.0541*	.01467	.000	-.0905	-.0202
Tamhane	4	6	.0140	.01634	.897	-.0262	.0519
		10	.0682*	.01541	.000	.0314	.1050
	6	4	-.0140	.01634	.897	-.0519	.0262
		10	.0541*	.01515	.001	.0192	.0916
	10	4	-.0682*	.01541	.000	-.1050	-.0314
		6	.0541*	.01515	.001	-.0916	-.0192

Based on observed means.
The error term is Mean Square(Error) = .136.

*. The mean difference is significant at the .05 level.

Rate each orientation based on your preference for each. Circle your answer.

	Down	Up	Left	Right
(not preferred) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(preferred) 5	5	5	5	5

Rate each orientation based on your perception of how fast you performed the task. Circle your answer.

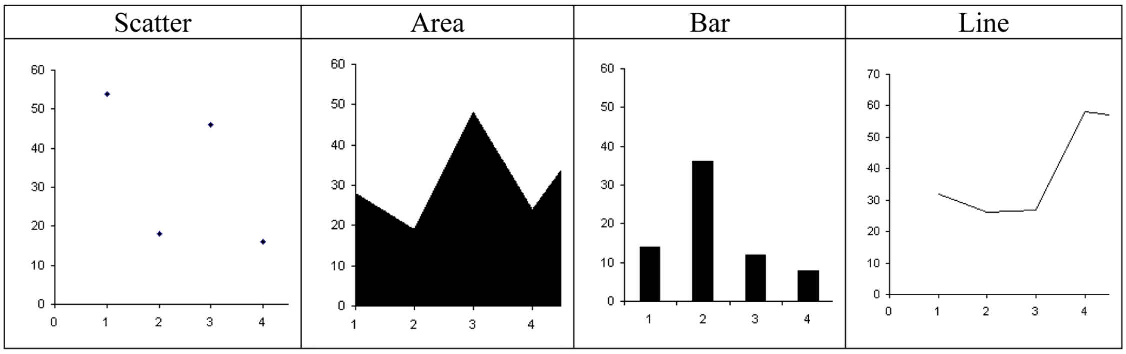
	Down	Up	Left	Right
(slowest) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(fastest) 5	5	5	5	5

Rate each orientation based on how difficult you feel it was. Circle your answer.

	Down	Up	Left	Right
(very difficult) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(easiest) 5	5	5	5	5

Figure 38: First set of questions of the post study questionnaire for experiment 1.

Graph examples



Rate graphs based on how difficult you feel they were for all four orientations. *Circle your answer.*

	Scatter	Area	Bar	Line
(not preferred) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(preferred) 5	5	5	5	5

Figure 39: Second set of questions of the post study questionnaire for experiment 1.

Frequencies (Orientation based on users preference)

Statistics

		0 degree	180 degree	90 degree	270 0 degree
N	Valid	40	40	40	40
	Missing	0	0	0	0
	Mean	4.62	2.65	2.52	2.68
	Median	5.00	3.00	3.00	3.00
	Std. Deviation	.667	1.001	1.012	1.118

Frequency Table

0 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	4	10.0	10.0	10.0
	4	7	17.5	17.5	27.5
	5	29	72.5	72.5	100.0
	Total	40	100.0	100.0	

180 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	12.5	12.5	12.5
	2	13	32.5	32.5	45.0
	3	14	35.0	35.0	80.0
	4	7	17.5	17.5	97.5
	5	1	2.5	2.5	100.0
	Total	40	100.0	100.0	

90 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	8	20.0	20.0	20.0
	2	10	25.0	25.0	45.0
	3	15	37.5	37.5	82.5
	4	7	17.5	17.5	100.0
	Total	40	100.0	100.0	

270 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	6	15.0	15.0	15.0
	2	13	32.5	32.5	47.5
	3	11	27.5	27.5	75.0
	4	8	20.0	20.0	95.0
	5	2	5.0	5.0	100.0
	Total	40	100.0	100.0	

Frequencies (How fast users performed the task)

Statistics

		0 degree	90 degree	180 degree	270 degree
N	Valid	40	40	40	40
	Missing	0	0	0	0
	Mean	4.45	3.05	2.70	2.88
	Median	5.00	3.00	3.00	3.00
	Std. Deviation	.815	1.154	1.067	1.137

Frequency Table

0 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	8	20.0	20.0	20.0
	4	6	15.0	15.0	35.0
	5	26	65.0	65.0	100.0
	Total	40	100.0	100.0	

180 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	4	10.0	10.0	10.0
	2	9	22.5	22.5	32.5
	3	12	30.0	30.0	62.5
	4	11	27.5	27.5	90.0
	5	4	10.0	10.0	100.0
	Total	40	100.0	100.0	

90 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	7	17.5	17.5	17.5
	2	9	22.5	22.5	40.0
	3	13	32.5	32.5	72.5
	4	11	27.5	27.5	100.0
	Total	40	100.0	100.0	

270 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	12.5	12.5	12.5
	2	10	25.0	25.0	37.5
	3	13	32.5	32.5	70.0
	4	9	22.5	22.5	92.5
	5	3	7.5	7.5	100.0
	Total	40	100.0	100.0	

Frequencies (How difficult the tasks were for users in each orientation)

Statistics

		0 degree	180 degree	90 degree	207 degree
N	Valid	40	40	40	40
	Missing	0	0	0	0
	Mean	4.45	2.85	2.58	2.60
	Median	5.00	3.00	2.00	3.00
	Std. Deviation	.714	1.051	.813	.841

Frequency Table

0 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	5	12.5	12.5	12.5
	4	12	30.0	30.0	42.5
	5	23	57.5	57.5	100.0
	Total	40	100.0	100.0	

90 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	3	7.5	7.5	7.5
	2	14	35.0	35.0	42.5
	3	11	27.5	27.5	70.0
	4	10	25.0	25.0	95.0
	5	2	5.0	5.0	100.0
	Total	40	100.0	100.0	

180 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2	5.0	5.0	5.0
	2	19	47.5	47.5	52.5
	3	13	32.5	32.5	85.0
	4	6	15.0	15.0	100.0
	Total	40	100.0	100.0	

270 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	3	7.5	7.5	7.5
	2	16	40.0	40.0	47.5
	3	15	37.5	37.5	85.0
	4	6	15.0	15.0	100.0
	Total	40	100.0	100.0	

Frequencies (Chart type that user prefere for all orientation)

Statistics

		Scatter	Area	Bar	Line
N	Valid	40	40	40	40
	Missing	0	0	0	0
	Mean	2.32	2.88	4.00	3.92
	Median	2.00	3.00	4.00	4.00
	Std. Deviation	1.328	1.244	1.132	1.071

Frequency Table

Scatter

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	12	30.0	30.0	30.0
	2	16	40.0	40.0	70.0
	3	4	10.0	10.0	80.0
	4	3	7.5	7.5	87.5
	5	5	12.5	12.5	100.0
	Total	40	100.0	100.0	

Area

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	8	20.0	20.0	20.0
	2	5	12.5	12.5	32.5
	3	15	37.5	37.5	70.0
	4	8	20.0	20.0	90.0
	5	4	10.0	10.0	100.0
	Total	40	100.0	100.0	

Bar

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	2.5	2.5	2.5
	2	4	10.0	10.0	12.5
	3	7	17.5	17.5	30.0
	4	10	25.0	25.0	55.0
	5	18	45.0	45.0	100.0
	Total	40	100.0	100.0	

Line

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	2.5	2.5	2.5
	2	3	7.5	7.5	10.0
	3	9	22.5	22.5	32.5
	4	12	30.0	30.0	62.5
	5	15	37.5	37.5	100.0
	Total	40	100.0	100.0	

Univariate Analysis of Variance (completion time)

Between-Subjects Factors

		Value Label	N
Chart_OrientationN	1	Down	486
	2	Up	424
	3	OA (Ref-out)	464
	4	OA (Ref-in)	472
Chart_TypeN	1	Line	896
	2	Bar	950
Different_In_Value	4	4 pixels	548
	6	6 pixels	633
	10	10 pixels	665
Standing	FALSE	Seating	920
	TRUE	Standing	926

Tests of Between-Subjects Effects

Dependent Variable:Time_In_MillSec

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.954E9	47	8.413E7	21.045	.000
Intercept	2.050E11	1	2.050E11	51272.255	.000
Chart_OrientationN	1.383E9	3	4.609E8	115.302	.000
Chart_TypeN	1.108E8	1	1.108E8	27.728	.000
Different_In_Value	2.055E9	2	1.027E9	257.022	.000
Standing	3.369E7	1	3.369E7	8.427	.004
Chart_OrientationN * Chart_TypeN	2331061.073	3	777020.358	.194	.900
Chart_OrientationN * Different_In_Value	3.631E7	6	6051691.303	1.514	.170
Chart_OrientationN * Standing	5.466E7	3	1.822E7	4.558	.003
Chart_TypeN * Different_In_Value	9.091E7	2	4.546E7	11.371	.000
Chart_TypeN * Standing	2666275.396	1	2666275.396	.667	.414
Different_In_Value * Standing	1.028E7	2	5141485.358	1.286	.277
Chart_OrientationN * Chart_TypeN * Different_In_Value	1.390E8	6	2.317E7	5.796	.000
Chart_OrientationN * Chart_TypeN * Standing	8236160.570	3	2745386.857	.687	.560
Chart_OrientationN * Different_In_Value * Standing	5688582.494	6	948097.082	.237	.964
Chart_TypeN * Different_In_Value * Standing	214360.558	2	107180.279	.027	.974
Chart_OrientationN * Chart_TypeN * Different_In_Value * Standing	3.037E7	6	5061952.108	1.266	.270

a. R Squared = .355 (Adjusted R Squared = .338)

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A.2 EXPERIMENT2

Tests of Between-Subjects Effects

Dependent Variable:Time_In_MillSec

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Error	7.188E9	1798	3997652.764		
Total	2.147E11	1846			
Corrected Total	1.114E10	1845			

a. R Squared = .355 (Adjusted R Squared = .338)

Estimated Marginal Means

1. Grand Mean

Dependent Variable:Time_In_MillSec

Mean	Std. Error	95% Confidence Interval	
		Lower Bound	Upper Bound
10627.766	46.935	10535.712	10719.820

2. Chart_OrientationN

Estimates

Dependent Variable:Time_In_MillSec

Chart_OrientationN	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Down	9429.027	90.906	9250.735	9607.319
Up	11915.425	98.272	11722.686	12108.164
OA (Ref-out)	10647.010	93.422	10463.782	10830.238
OA (Ref-in)	10519.602	92.726	10337.741	10701.463

Pairwise Comparisons

Dependent Variable:Time_In_MillSec

(I) Chart_OrientationN	(J) Chart_OrientationN	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
Down	Up	-2486.398*	133.870	.000	-2839.974	-2132.823
	OA (Ref-out)	-1217.983*	130.352	.000	-1562.265	-873.701
	OA (Ref-in)	-1090.575*	129.853	.000	-1433.541	-747.609
Up	Down	2486.398*	133.870	.000	2132.823	2839.974
	OA (Ref-out)	1268.415*	135.592	.000	910.294	1626.537
	OA (Ref-in)	1395.824*	135.112	.000	1038.967	1752.680
OA (Ref-out)	Down	1217.983*	130.352	.000	873.701	1562.265

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

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A.2 EXPERIMENT2

Pairwise Comparisons

Dependent Variable:Time_In_MillSec

(I) Chart_OrientationN	(J) Chart_OrientationN	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
OA (Ref-out)	Up	-1268.415*	135.592	.000	-1626.537	-910.294
	OA (Ref-in)	127.408	131.627	1.000	-220.243	475.060
OA (Ref-in)	Down	1090.575*	129.853	.000	747.609	1433.541
	Up	-1395.824*	135.112	.000	-1752.680	-1038.967
	OA (Ref-out)	-127.408	131.627	1.000	-475.060	220.243

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Time_In_MillSec

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	1.383E9	3	4.609E8	115.302	.000
Error	7.188E9	1798	3997652.764		

The F tests the effect of Chart_OrientationN. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

3. Chart_TypeN

Estimates

Dependent Variable:Time_In_MillSec

Chart_TypeN	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Line	10874.918	67.477	10742.577	11007.258
Bar	10380.614	65.258	10252.624	10508.605

Pairwise Comparisons

Dependent Variable:Time_In_MillSec

(I) Chart_TypeN	(J) Chart_TypeN	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
Line	Bar	494.303*	93.871	.000	310.196	678.410
Bar	Line	-494.303*	93.871	.000	-678.410	-310.196

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Time_In_MillSec

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	1.108E8	1	1.108E8	27.728	.000
Error	7.188E9	1798	3997652.764		

The F tests the effect of Chart_TypeN. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

4. Different_In_Value

Estimates

Dependent Variable:Time_In_MillSec

Different_In_Value	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
4 pixels	11877.637	86.259	11708.458	12046.815
6 pixels	10736.337	79.686	10580.050	10892.624
10 pixels	9269.324	77.691	9116.949	9421.699

Pairwise Comparisons

Dependent Variable:Time_In_MillSec

(I) Different_In_Value	(J) Different_In_Value	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
4 pixels	6 pixels	1141.300*	117.433	.000	859.905	1422.695
	10 pixels	2608.313*	116.089	.000	2330.139	2886.487
6 pixels	4 pixels	-1141.300*	117.433	.000	-1422.695	-859.905
	10 pixels	1467.013*	111.291	.000	1200.334	1733.692
10 pixels	4 pixels	-2608.313*	116.089	.000	-2886.487	-2330.139
	6 pixels	-1467.013*	111.291	.000	-1733.692	-1200.334

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Time_In_MillSec

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	2.055E9	2	1.027E9	257.022	.000
Error	7.188E9	1798	3997652.764		

The F tests the effect of Different_In_Value. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

5. Standing

Estimates

Dependent Variable:Time_In_MillSec

Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Seating	10764.019	66.603	10633.391	10894.647
Standing	10491.513	66.149	10361.775	10621.251

Pairwise Comparisons

Dependent Variable:Time_In_MillSec

(I) Standing	(J) Standing	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	95% Confidence Interval for Difference[a] Upper Bound
Seating	Standing	272.507*	93.871	.004	88.399	456.614
Standing	Seating	-272.507*	93.871	.004	-456.614	-88.399

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Time_In_MillSec

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	3.369E7	1	3.369E7	8.427	.004
Error	7.188E9	1798	3997652.764		

The F tests the effect of Standing. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

6. Chart_OrientationN * Chart_TypeN

Dependent Variable:Time_In_MillSec

Chart_OrientationN	Chart_TypeN	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Line	9658.105	128.148	9406.770	9909.439
	Bar	9199.949	128.971	8947.001	9452.898
Up	Line	12223.301	141.446	11945.886	12500.716
	Bar	11607.550	136.465	11339.904	11875.196
OA (Ref-out)	Line	10888.575	136.361	10621.132	11156.017
	Bar	10405.445	127.736	10154.918	10655.972
OA (Ref-in)	Line	10729.690	133.515	10467.828	10991.551
	Bar	10309.514	128.708	10057.081	10561.946

7. Chart_OrientationN * Different_In_Value

Dependent Variable:Time_In_MillSec

Chart_Orientat...	Different_In_Value	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	4 pixels	10824.007	162.505	10505.288	11142.726
	6 pixels	9673.647	155.873	9367.936	9979.359
	10 pixels	7789.427	153.851	7487.680	8091.173

7. Chart_OrientationN * Different_In_Value

Dependent Variable:Time_In_MillSec

Chart_ Orientation N	Different _In_ Value	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Up	4 pixels	12959.034	185.831	12594.566	13323.502
	6 pixels	12011.741	163.324	11691.416	12332.066
	10 pixels	10775.501	160.338	10461.033	11089.969
OA (Ref-out)	4 pixels	11847.278	171.240	11511.428	12183.128
	6 pixels	10739.631	159.405	10426.992	11052.270
	10 pixels	9354.121	154.325	9051.445	9656.797
OA (Ref-in)	4 pixels	11880.229	169.663	11547.470	12212.987
	6 pixels	10520.328	158.796	10208.885	10831.772
	10 pixels	9158.248	152.907	8858.354	9458.142

8. Chart_OrientationN * Standing

Dependent Variable:Time_In_MillSec

Chart_ Orientation N	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Down	Seating	9584.562	126.803	9335.865	9833.260
	Standing	9273.492	130.293	9017.950	9529.033
Up	Seating	12205.138	138.250	11933.991	12476.285
	Standing	11625.713	139.701	11351.719	11899.707
OA (Ref-out)	Seating	10493.711	131.985	10234.851	10752.571
	Standing	10800.309	132.253	10540.923	11059.695
OA (Ref-in)	Seating	10772.666	135.513	10506.886	11038.446
	Standing	10266.538	126.603	10018.234	10514.842

9. Chart_TypeN * Different_In_Value

Dependent Variable:Time_In_MillSec

Chart _Typ eN	Different _In_ Value	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Line	4 pixels	12398.838	124.280	12155.090	12642.586
	6 pixels	10699.326	114.686	10474.395	10924.258
	10 pixels	9526.589	111.263	9308.370	9744.807
Bar	4 pixels	11356.436	119.654	11121.761	11591.111
	6 pixels	10773.348	110.664	10556.305	10990.391
	10 pixels	9012.060	108.464	8799.331	9224.788

10. Chart_TypeN * Standing

Dependent Variable:Time_In_MillSec

Chart _Typ eN	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Line	Seating	10972.840	96.500	10783.576	11162.104
	Standing	10776.995	94.340	10591.967	10962.024
Bar	Seating	10555.199	91.824	10375.105	10735.293
	Standing	10206.030	92.752	10024.118	10387.942

11. Different_In_Value * Standing

Dependent Variable:Time_In_MillSec

Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
4 pixels	Seating	12112.958	123.485	11870.770	12355.147
	Standing	11642.316	120.474	11406.032	11878.600
6 pixels	Seating	10783.540	112.855	10562.199	11004.880
	Standing	10689.134	112.530	10468.430	10909.838
10 pixels	Seating	9395.560	109.267	9181.257	9609.863
	Standing	9143.088	110.474	8926.417	9359.760

12. Chart_OrientationN * Chart_TypeN * Different_In_Value

Dependent Variable:Time_In_MillSec

Chart_OrientationN	Chart_TypeN	Different_In_Value	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Line	4 pixels	11784.279	224.970	11343.049	12225.508
		6 pixels	9625.321	221.392	9191.109	10059.533
		10 pixels	7564.715	219.480	7134.252	7995.177
	Bar	4 pixels	9863.735	234.564	9403.688	10323.783
		6 pixels	9721.974	219.480	9291.511	10152.436
		10 pixels	8014.139	215.661	7591.167	8437.110
Up	Line	4 pixels	13036.731	266.849	12513.365	13560.097
		6 pixels	12052.071	234.036	11593.061	12511.082
		10 pixels	11581.100	232.553	11124.997	12037.202
	Bar	4 pixels	12881.337	258.699	12373.955	13388.719
		6 pixels	11971.411	227.873	11524.486	12418.336
		10 pixels	9969.902	220.798	9536.854	10402.951
OA (Ref-out)	Line	4 pixels	12269.027	254.058	11770.747	12767.307
		6 pixels	10739.851	232.427	10283.996	11195.707
		10 pixels	9656.846	220.864	9223.669	10090.023
	Bar	4 pixels	11425.529	229.667	10975.087	11875.971
		6 pixels	10739.411	218.216	10311.428	11167.394
		10 pixels	9051.395	215.602	8628.538	9474.253
OA (Ref-in)	Line	4 pixels	12505.314	246.501	12021.855	12988.773
		6 pixels	10380.062	229.427	9930.090	10830.033
		10 pixels	9303.694	216.882	8878.327	9729.061
	Bar	4 pixels	11255.143	233.195	10797.782	11712.505
		6 pixels	10660.595	219.608	10229.882	11091.308
		10 pixels	9012.802	215.602	8589.945	9435.660

13. Chart_OrientationN * Chart_TypeN * Standing

Dependent Variable:Time_In_MillSec

Chart_Orientat...	Chart_TypeN	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Line	Seating	9784.537	178.257	9434.925	10134.149
		Standing	9531.672	184.152	9170.497	9892.848
	Bar	Seating	9384.587	180.391	9030.789	9738.385

13. Chart_OrientationN * Chart_TypeN * Standing

Dependent Variable:Time_In_MillSec

Chart_ OrientationN	Chart_TypeN	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Bar	Standing	9015.311	184.372	8653.705	9376.917
Up	Line	Seating	12389.326	200.868	11995.366	12783.286
		Standing	12057.275	199.197	11666.594	12447.956
	Bar	Seating	12020.950	190.010	11648.286	12393.613
		Standing	11194.151	195.925	10809.886	11578.415
OA (Ref-out)	Line	Seating	10670.675	194.719	10288.775	11052.575
		Standing	11106.475	190.949	10731.970	11480.980
	Bar	Seating	10316.747	178.225	9967.197	10666.298
		Standing	10494.143	183.036	10135.158	10853.127
OA (Ref-in)	Line	Seating	11046.821	197.375	10659.713	11433.928
		Standing	10412.559	179.858	10059.807	10765.311
	Bar	Seating	10498.511	185.738	10134.225	10862.796
		Standing	10120.516	178.225	9770.966	10470.067

14. Chart_OrientationN * Different_In_Value * Standing

Dependent Variable:Time_In_MillSec

Chart_ OrientationN	Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	4 pixels	Seating	11045.638	224.970	10604.408	11486.867
		Standing	10602.376	234.564	10142.329	11062.424
	6 pixels	Seating	9758.049	215.661	9335.078	10181.021
		Standing	9589.246	225.114	9147.733	10030.758
	10 pixels	Seating	7950.000	218.154	7522.138	8377.862
		Standing	7628.853	217.002	7203.251	8054.456
Up	4 pixels	Seating	13417.716	266.849	12894.350	13941.082
		Standing	12500.353	258.699	11992.971	13007.734
	6 pixels	Seating	12154.817	229.428	11704.844	12604.790
		Standing	11868.665	232.512	11412.643	12324.687
	10 pixels	Seating	11042.882	219.480	10612.419	11473.344
		Standing	10508.120	233.797	10049.578	10966.663
OA (Ref-out)	4 pixels	Seating	11729.171	241.452	11255.615	12202.727
		Standing	11965.385	242.885	11489.019	12441.752
	6 pixels	Seating	10611.135	224.173	10171.469	11050.802
		Standing	10868.127	226.687	10423.528	11312.725
	10 pixels	Seating	9140.827	219.608	8710.114	9571.540
		Standing	9567.414	216.882	9142.048	9992.781
OA (Ref-in)	4 pixels	Seating	12259.309	252.699	11763.694	12754.925
		Standing	11501.148	226.463	11056.989	11945.307
	6 pixels	Seating	10610.157	233.195	10152.795	11067.518
		Standing	10430.500	215.602	10007.643	10853.357
	10 pixels	Seating	9448.531	216.882	9023.164	9873.898
		Standing	8867.965	215.602	8445.108	9290.822

15. Chart_TypeN * Different_In_Value * Standing

Dependent Variable:Time_In_MillSec

Chart_TypeN	Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Line	4 pixels	Seating	12580.187	182.166	12222.907	12937.467
		Standing	12217.488	169.108	11885.820	12549.157
	6 pixels	Seating	10714.123	162.889	10394.652	11033.594
		Standing	10684.529	161.489	10367.803	11001.256
	10 pixels	Seating	9624.209	155.219	9319.780	9928.638
		Standing	9428.968	159.451	9116.239	9741.698
Bar	4 pixels	Seating	11645.730	166.761	11318.663	11972.796
		Standing	11067.143	171.635	10730.517	11403.768
	6 pixels	Seating	10852.956	156.244	10546.517	11159.395
		Standing	10693.739	156.760	10386.289	11001.189
	10 pixels	Seating	9166.911	153.831	8865.205	9468.617
		Standing	8857.208	152.950	8557.231	9157.186

16. Chart_OrientationN * Chart_TypeN * Different_In_Value * Standing

Dependent Variable:Time_In_MillSec

Chart_OrientationN	Chart_TypeN	Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Down	Line	4 pixels	Seating	11984.275	316.135	11364.244	12604.306
			Standing	11584.282	320.162	10956.353	12212.211
		6 pixels	Seating	9702.932	301.423	9111.756	10294.108
			Standing	9547.711	324.348	8911.573	10183.848
		10 pixels	Seating	7666.405	308.516	7061.317	8271.493
			Standing	7463.024	312.256	6850.602	8075.447
	Bar	4 pixels	Seating	10107.000	320.162	9479.071	10734.929
			Standing	9620.471	342.897	8947.953	10292.988
		6 pixels	Seating	9813.167	308.516	9208.079	10418.255
			Standing	9630.780	312.256	9018.358	10243.203
		10 pixels	Seating	8233.595	308.516	7628.507	8838.683
			Standing	7794.682	301.423	7203.506	8385.858
Up	Line	4 pixels	Seating	13081.400	399.883	12297.117	13865.683
			Standing	12992.063	353.450	12298.847	13685.278
		6 pixels	Seating	12089.865	328.701	11445.188	12734.542
			Standing	12014.278	333.236	11360.708	12667.847
		10 pixels	Seating	11996.714	308.516	11391.626	12601.802
			Standing	11165.485	348.053	10482.854	11848.116
	Bar	4 pixels	Seating	13754.031	353.450	13060.816	14447.246
			Standing	12008.643	377.854	11267.565	12749.721
		6 pixels	Seating	12219.769	320.162	11591.840	12847.699
			Standing	11723.053	324.348	11086.915	12359.191
		10 pixels	Seating	10089.049	312.256	9476.626	10701.471
			Standing	9850.756	312.256	9238.334	10463.179
OA (Ref-out)	Line	4 pixels	Seating	12260.867	365.041	11544.917	12976.816
			Standing	12277.188	353.450	11583.972	12970.403

16. Chart_OrientationN * Chart_TypeN * Different_In_Value * Standing

Dependent Variable:Time_In_MillSec

Chart_ OrientationN	Chart _TypeN	Different _In_ Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
OA (Ref-out)	Line	6 pixels	Seating	10475.108	328.701	9830.431	11119.785
			Standing	11004.595	328.701	10359.918	11649.272
		10 pixels	Seating	9276.050	316.135	8656.019	9896.081
			Standing	10037.643	308.516	9432.555	10642.731
	Bar	4 pixels	Seating	11197.475	316.135	10577.444	11817.506
			Standing	11653.583	333.236	11000.014	12307.153
		6 pixels	Seating	10747.163	304.908	10149.152	11345.173
			Standing	10731.659	312.256	10119.236	11344.081
		10 pixels	Seating	9005.605	304.908	8407.594	9603.615
			Standing	9097.186	304.908	8499.175	9695.197
OA (Ref-in)	Line	4 pixels	Seating	12994.207	371.282	12266.018	13722.396
			Standing	12016.421	324.348	11380.283	12652.559
		6 pixels	Seating	10588.588	342.897	9916.071	11261.106
			Standing	10171.535	304.908	9573.524	10769.545
		10 pixels	Seating	9557.667	308.516	8952.579	10162.755
			Standing	9049.721	304.908	8451.710	9647.731
	Bar	4 pixels	Seating	11524.412	342.897	10851.894	12196.929
			Standing	10985.875	316.135	10365.844	11605.906
		6 pixels	Seating	10631.725	316.135	10011.694	11251.756
			Standing	10689.465	304.908	10091.455	11287.476
		10 pixels	Seating	9339.395	304.908	8741.385	9937.406
			Standing	8686.209	304.908	8088.199	9284.220

Post Hoc Tests

Chart_OrientationN

Multiple Comparisons

Dependent Variable:Time_In_MillSec

	(I) Chart_ OrientationN	(J) Chart_ OrientationN	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	Down	Up	-2423.22*	132.869	.000	-2774.15	-2072.29
		OA (Ref-out)	-1156.89*	129.774	.000	-1499.64	-814.13
		OA (Ref-in)	-1013.31*	129.210	.000	-1354.57	-672.04
	Up	Down	2423.22*	132.869	.000	2072.29	2774.15
		OA (Ref-out)	1266.33*	134.328	.000	911.54	1621.11
		OA (Ref-in)	1409.91*	133.784	.000	1056.56	1763.26
	OA (Ref-out)	Down	1156.89*	129.774	.000	814.13	1499.64

Based on observed means.
The error term is Mean Square(Error) = 3997652.764.

*. The mean difference is significant at the .05 level.

Multiple Comparisons

Dependent Variable:Time_In_MillSec

	(I) Chart_Orientation N	(J) Chart_Orientation N	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	OA (Ref-out)	Up	-1266.33*	134.328	.000	-1621.11	-911.54
		OA (Ref-in)	143.58	130.710	1.000	-201.65	488.81
	OA (Ref-in)	Down	1013.31*	129.210	.000	672.04	1354.57
		Up	-1409.91*	133.784	.000	-1763.26	-1056.56
		OA (Ref-out)	-143.58	130.710	1.000	-488.81	201.65
Tamhane	Down	Up	-2423.22*	156.473	.000	-2835.84	-2010.60
		OA (Ref-out)	-1156.89*	149.524	.000	-1551.12	-762.66
		OA (Ref-in)	-1013.31*	145.624	.000	-1397.25	-629.37
	Up	Down	2423.22*	156.473	.000	2010.60	2835.84
		OA (Ref-out)	1266.33*	159.044	.000	846.92	1685.73
		OA (Ref-in)	1409.91*	155.384	.000	1000.15	1819.67
	OA (Ref-out)	Down	1156.89*	149.524	.000	762.66	1551.12
		Up	-1266.33*	159.044	.000	-1685.73	-846.92
		OA (Ref-in)	143.58	148.384	.912	-247.65	534.82
	OA (Ref-in)	Down	1013.31*	145.624	.000	629.37	1397.25
		Up	-1409.91*	155.384	.000	-1819.67	-1000.15
		OA (Ref-out)	-143.58	148.384	.912	-534.82	247.65

Based on observed means.
The error term is Mean Square(Error) = 3997652.764.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

Different_In_Value

Multiple Comparisons

Dependent Variable:Time_In_MillSec

	(I) Different_In_Value	(J) Different_In_Value	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	4 pixels	6 pixels	1088.93*	116.664	.000	809.38	1368.49
		10 pixels	2558.34*	115.354	.000	2281.92	2834.75
	6 pixels	4 pixels	-1088.93*	116.664	.000	-1368.49	-809.38
		10 pixels	1469.40*	111.027	.000	1203.36	1735.45
	10 pixels	4 pixels	-2558.34*	115.354	.000	-2834.75	-2281.92
		6 pixels	-1469.40*	111.027	.000	-1735.45	-1203.36
Tamhane	4 pixels	6 pixels	1088.93*	132.755	.000	771.48	1406.39
		10 pixels	2558.34*	130.317	.000	2246.71	2869.96

Based on observed means.
The error term is Mean Square(Error) = 3997652.764.

*. The mean difference is significant at the .05 level.

Multiple Comparisons

Dependent Variable:Time_In_MillSec

	(I) Different _In_ Value	(J) Different _In_ Value	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tamhane	6 pixels	4 pixels	-1088.93*	132.755	.000	-1406.39	-771.48
		10 pixels	1469.40*	120.917	.000	1180.31	1758.50
	10 pixels	4 pixels	-2558.34*	130.317	.000	-2869.96	-2246.71
		6 pixels	-1469.40*	120.917	.000	-1758.50	-1180.31

Based on observed means.
The error term is Mean Square(Error) = 3997652.764.

*. The mean difference is significant at the .05 level.

Univariate Analysis of Variance (error rate)

Between-Subjects Factors

		Value Label	N
Chart_OrientationN	1	Down	530
	2	Up	510
	3	OA (Ref-out)	534
	4	OA (Ref-in)	538
Chart_TypeN	1	Line	1059
	2	Bar	1053
Different_In_Value	4	4 pixels	687
	6	6 pixels	711
	10	10 pixels	714
Standing	FALSE	Seating	1047
	TRUE	Standing	1065

Tests of Between-Subjects Effects

Dependent Variable:Error

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	17.402[a]	47	.370	3.553	.000
Intercept	34.078	1	34.078	327.006	.000
Chart_OrientationN	2.066	3	.689	6.610	.000
Chart_TypeN	1.656	1	1.656	15.888	.000
Different_In_Value	6.647	2	3.323	31.891	.000
Standing	.044	1	.044	.426	.514
Chart_OrientationN * Chart_TypeN	.772	3	.257	2.468	.060
Chart_OrientationN * Different_In_Value	.624	6	.104	.998	.425
Chart_OrientationN * Standing	2.429	3	.810	7.770	.000
Chart_TypeN * Different_In_Value	.036	2	.018	.171	.842
Chart_TypeN * Standing	.128	1	.128	1.226	.268
Different_In_Value * Standing	.084	2	.042	.404	.668
Chart_OrientationN * Chart_TypeN * Different_In_Value	.737	6	.123	1.178	.315
Chart_OrientationN * Chart_TypeN * Standing	.272	3	.091	.869	.456
Chart_OrientationN * Different_In_Value * Standing	1.023	6	.170	1.636	.133
Chart_TypeN * Different_In_Value * Standing	.564	2	.282	2.706	.067
Chart_OrientationN * Chart_TypeN * Different_In_Value * Standing	.472	6	.079	.755	.605

a. R Squared = .075 (Adjusted R Squared = .054)

Tests of Between-Subjects Effects

Dependent Variable:Error

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Error	215.096	2064	.104		
Total	266.000	2112			
Corrected Total	232.498	2111			

a. R Squared = .075 (Adjusted R Squared = .054)

Estimated Marginal Means

1. Grand Mean

Dependent Variable:Error

Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
.127	.007	.113	.141

2. Chart_OrientationN

Estimates

Dependent Variable:Error

Chart_ OrientationN	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	.083	.014	.056	.111
Up	.172	.014	.144	.200
OA (Ref-out)	.131	.014	.104	.158
OA (Ref-in)	.122	.014	.095	.150

Pairwise Comparisons

Dependent Variable:Error

(I) Chart_ OrientationN	(J) Chart_ OrientationN	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	95% Confidence Interval for Difference[a] Upper Bound
Down	Up	-.089*	.020	.000	-.142	-.036
	OA (Ref-out)	-.048	.020	.094	-.100	.004
	OA (Ref-in)	-.039	.020	.281	-.091	.013
Up	Down	.089*	.020	.000	.036	.142
	OA (Ref-out)	.041	.020	.245	-.012	.094
	OA (Ref-in)	.050	.020	.079	-.003	.102
OA (Ref-out)	Down	.048	.020	.094	-.004	.100
	Up	-.041	.020	.245	-.094	.012
	OA (Ref-in)	.009	.020	1.000	-.043	.061
OA (Ref-in)	Down	.039	.020	.281	-.013	.091

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Pairwise Comparisons

Dependent Variable:Error

(I) Chart_OrientationN	(J) Chart_OrientationN	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
OA (Ref-in)	Up	-.050	.020	.079	-.102	.003
	OA (Ref-out)	-.009	.020	1.000	-.061	.043

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	2.066	3	.689	6.610	.000
Error	215.096	2064	.104		

The F tests the effect of Chart_OrientationN. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

3. Chart_TypeN

Estimates

Dependent Variable:Error

Chart_TypeN	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Line	.155	.010	.136	.175
Bar	.099	.010	.080	.119

Pairwise Comparisons

Dependent Variable:Error

(I) Chart_TypeN	(J) Chart_TypeN	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
Line	Bar	.056*	.014	.000	.028	.084
Bar	Line	-.056*	.014	.000	-.084	-.028

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	1.656	1	1.656	15.888	.000

The F tests the effect of Chart_TypeN. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Error	215.096	2064	.104		

The F tests the effect of Chart_TypeN. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

4. Different_In_Value

Estimates

Dependent Variable:Error

Different _In_ Value	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
4 pixels	.203	.012	.179	.228
6 pixels	.110	.012	.086	.133
10 pixels	.068	.012	.045	.092

Pairwise Comparisons

Dependent Variable:Error

(I) Different _In_ Value	(J) Different _In_ Value	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
4 pixels	6 pixels	.094*	.017	.000	.052	.135
	10 pixels	.135*	.017	.000	.093	.176
6 pixels	4 pixels	-.094*	.017	.000	-.135	-.052
	10 pixels	.041*	.017	.049	.000	.082
10 pixels	4 pixels	-.135*	.017	.000	-.176	-.093
	6 pixels	-.041*	.017	.049	-.082	.000

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	6.647	2	3.323	31.891	.000
Error	215.096	2064	.104		

The F tests the effect of Different_In_Value. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

5. Standing

Estimates

Dependent Variable:Error

Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Seating	.123	.010	.103	.142
Standing	.132	.010	.112	.151

Pairwise Comparisons

Dependent Variable:Error

(I) Standing	(J) Standing	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	95% Confidence Interval for Difference[a] Upper Bound
Seating	Standing	-.009	.014	.514	-.037	.018
Standing	Seating	.009	.014	.514	-.018	.037

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable:Error

	Sum of Squares	df	Mean Square	F	Sig.
Contrast	.044	1	.044	.426	.514
Error	215.096	2064	.104		

The F tests the effect of Standing. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

6. Chart_OrientationN * Chart_TypeN

Dependent Variable:Error

Chart_ OrientationN	Chart _TypeN	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Line	.082	.020	.043	.121
	Bar	.084	.020	.045	.123
Up	Line	.203	.020	.163	.243
	Bar	.141	.020	.101	.181
OA (Ref-out)	Line	.184	.020	.145	.222
	Bar	.078	.020	.040	.117
OA (Ref-in)	Line	.152	.020	.113	.190
	Bar	.093	.020	.054	.132

7. Chart_OrientationN * Different_In_Value

Dependent Variable:Error

Chart _Orientat...	Different _In_ Value	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	4 pixels	.121	.025	.073	.169
	6 pixels	.078	.024	.031	.125
	10 pixels	.051	.024	.003	.098
Up	4 pixels	.251	.026	.201	.302

7. Chart_OrientationN * Different_In_Value

Dependent Variable:Error

Chart_OrientationN	Different_In_Value	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Up	6 pixels	.147	.024	.100	.195
	10 pixels	.117	.024	.070	.165
OA (Ref-out)	4 pixels	.224	.024	.177	.272
	6 pixels	.107	.024	.059	.155
	10 pixels	.062	.024	.014	.109
OA (Ref-in)	4 pixels	.217	.024	.169	.264
	6 pixels	.106	.024	.059	.153
	10 pixels	.045	.024	-.003	.092

8. Chart_OrientationN * Standing

Dependent Variable:Error

Chart_OrientationN	Standing	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Down	Seating	.050	.020	.011	.089
	Standing	.116	.020	.078	.155
Up	Seating	.145	.020	.105	.185
	Standing	.199	.020	.160	.238
OA (Ref-out)	Seating	.121	.020	.082	.160
	Standing	.141	.020	.102	.180
OA (Ref-in)	Seating	.174	.020	.136	.213
	Standing	.070	.020	.032	.109

9. Chart_TypeN * Different_In_Value

Dependent Variable:Error

Chart_TypeN	Different_In_Value	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Line	4 pixels	.230	.017	.196	.265
	6 pixels	.143	.017	.110	.177
	10 pixels	.092	.017	.059	.126
Bar	4 pixels	.176	.017	.142	.211
	6 pixels	.076	.017	.042	.110
	10 pixels	.045	.017	.011	.078

10. Chart_TypeN * Standing

Dependent Variable:Error

Chart_TypeN	Standing	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Line	Seating	.158	.014	.131	.186
	Standing	.152	.014	.125	.179
Bar	Seating	.087	.014	.059	.114
	Standing	.111	.014	.084	.139

11. Different_In_Value * Standing

Dependent Variable:Error

Different _In_ Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
4 pixels	Seating	.207	.018	.172	.241
	Standing	.200	.017	.166	.234
6 pixels	Seating	.105	.017	.071	.138
	Standing	.115	.017	.081	.148
10 pixels	Seating	.056	.017	.023	.090
	Standing	.081	.017	.047	.114

12. Chart_OrientationN * Chart_TypeN * Different_In_Value

Dependent Variable:Error

Chart_ Orientation N	Chart _Typ eN	Different _In_ Value	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Down	Line	4 pixels	.090	.035	.023	.158
		6 pixels	.089	.034	.022	.156
		10 pixels	.067	.034	6.024E-5	.134
	Bar	4 pixels	.151	.035	.083	.219
		6 pixels	.067	.034	6.024E-5	.134
		10 pixels	.034	.034	-.033	.101
Up	Line	4 pixels	.272	.037	.200	.344
		6 pixels	.170	.034	.103	.238
		10 pixels	.167	.034	.100	.233
	Bar	4 pixels	.231	.037	.159	.302
		6 pixels	.124	.034	.057	.192
		10 pixels	.068	.034	.000	.135
OA (Ref-out)	Line	4 pixels	.304	.034	.236	.371
		6 pixels	.168	.034	.101	.236
		10 pixels	.079	.034	.012	.146
	Bar	4 pixels	.145	.034	.078	.213
		6 pixels	.045	.034	-.022	.113
		10 pixels	.044	.034	-.022	.111
OA (Ref-in)	Line	4 pixels	.256	.034	.189	.322
		6 pixels	.144	.034	.078	.211
		10 pixels	.056	.034	-.011	.122
	Bar	4 pixels	.178	.034	.111	.245
		6 pixels	.068	.034	.001	.135
		10 pixels	.034	.034	-.034	.101

13. Chart_OrientationN * Chart_TypeN * Standing

Dependent Variable:Error

Chart _Orie ntat...	Chart _Typ eN	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Down	Line	Seating	.038	.028	-.017	.094
		Standing	.126	.028	.071	.180
	Bar	Seating	.061	.028	.006	.117

13. Chart_OrientationN * Chart_TypeN * Standing

Dependent Variable:Error

Chart_ OrientationN	Chart _TypeN	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Bar	Standing	.107	.028	.052	.162
Up	Line	Seating	.183	.029	.127	.240
		Standing	.223	.028	.167	.278
	Bar	Seating	.106	.029	.050	.163
		Standing	.175	.028	.120	.231
OA (Ref-out)	Line	Seating	.189	.028	.134	.244
		Standing	.178	.028	.123	.232
	Bar	Seating	.053	.028	-.002	.108
		Standing	.104	.028	.050	.159
OA (Ref-in)	Line	Seating	.222	.028	.168	.277
		Standing	.081	.028	.027	.136
	Bar	Seating	.127	.028	.072	.181
		Standing	.059	.028	.005	.114

14. Chart_OrientationN * Different_In_Value * Standing

Dependent Variable:Error

Chart_ OrientationN	Different _In_ Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	4 pixels	Seating	.070	.035	.002	.139
		Standing	.171	.034	.104	.239
	6 pixels	Seating	.034	.034	-.033	.101
		Standing	.122	.034	.055	.189
	10 pixels	Seating	.045	.034	-.022	.113
		Standing	.056	.034	-.011	.122
Up	4 pixels	Seating	.252	.037	.179	.325
		Standing	.251	.036	.180	.322
	6 pixels	Seating	.126	.035	.058	.194
		Standing	.169	.034	.102	.236
	10 pixels	Seating	.057	.034	-.011	.124
		Standing	.178	.034	.111	.245
OA (Ref-out)	4 pixels	Seating	.205	.034	.137	.272
		Standing	.244	.034	.178	.311
	6 pixels	Seating	.091	.034	.023	.158
		Standing	.123	.034	.056	.190
	10 pixels	Seating	.068	.034	.001	.135
		Standing	.056	.034	-.011	.122
OA (Ref-in)	4 pixels	Seating	.300	.034	.233	.367
		Standing	.133	.034	.067	.200
	6 pixels	Seating	.168	.034	.101	.235
		Standing	.044	.034	-.022	.111
	10 pixels	Seating	.056	.034	-.011	.122
		Standing	.034	.034	-.034	.101

15. Chart_TypeN * Different_In_Value * Standing

Dependent Variable:Error

Chart_TypeN	Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Line	4 pixels	Seating	.261	.025	.212	.310
		Standing	.199	.024	.152	.247
	6 pixels	Seating	.146	.024	.099	.194
		Standing	.140	.024	.093	.187
	10 pixels	Seating	.067	.024	.020	.115
		Standing	.117	.024	.069	.164
Bar	4 pixels	Seating	.152	.025	.103	.200
		Standing	.201	.025	.152	.249
	6 pixels	Seating	.063	.024	.015	.111
		Standing	.089	.024	.042	.137
	10 pixels	Seating	.045	.024	-.002	.093
		Standing	.045	.024	-.003	.092

16. Chart_OrientationN * Chart_TypeN * Different_In_Value * Standing

Dependent Variable:Error

Chart_OrientationN	Chart_TypeN	Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Down	Line	4 pixels	Seating	.048	.050	-.050	.145
			Standing	.133	.048	.039	.228
		6 pixels	Seating	.022	.048	-.072	.117
			Standing	.156	.048	.061	.250
		10 pixels	Seating	.045	.049	-.050	.141
			Standing	.089	.048	-.005	.183
	Bar	4 pixels	Seating	.093	.049	-.004	.190
			Standing	.209	.049	.113	.306
		6 pixels	Seating	.045	.049	-.050	.141
			Standing	.089	.048	-.005	.183
		10 pixels	Seating	.045	.049	-.050	.141
			Standing	.022	.048	-.072	.117
Up	Line	4 pixels	Seating	.324	.053	.220	.428
			Standing	.220	.050	.121	.318
		6 pixels	Seating	.159	.049	.064	.255
			Standing	.182	.049	.086	.277
		10 pixels	Seating	.067	.048	-.028	.161
			Standing	.267	.048	.172	.361
	Bar	4 pixels	Seating	.179	.052	.078	.281
			Standing	.282	.052	.181	.383
		6 pixels	Seating	.093	.049	-.004	.190
			Standing	.156	.048	.061	.250
		10 pixels	Seating	.047	.049	-.050	.143
			Standing	.089	.048	-.005	.183
OA (Ref-out)	Line	4 pixels	Seating	.318	.049	.223	.414
			Standing	.289	.048	.195	.383

16. Chart_OrientationN * Chart_TypeN * Different_In_Value * Standing

Dependent Variable:Error

Chart_ OrientationN	Chart_TypeN	Different_In_Value	Standing	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
OA (Ref-out)	Line	6 pixels	Seating	.159	.049	.064	.255
			Standing	.178	.048	.083	.272
		10 pixels	Seating	.091	.049	-.005	.186
			Standing	.067	.048	-.028	.161
	Bar	4 pixels	Seating	.091	.049	-.005	.186
			Standing	.200	.048	.106	.294
		6 pixels	Seating	.023	.049	-.073	.118
			Standing	.068	.049	-.027	.164
		10 pixels	Seating	.044	.048	-.050	.139
			Standing	.044	.048	-.050	.139
OA (Ref-in)	Line	4 pixels	Seating	.356	.048	.261	.450
			Standing	.156	.048	.061	.250
		6 pixels	Seating	.244	.048	.150	.339
			Standing	.044	.048	-.050	.139
		10 pixels	Seating	.067	.048	-.028	.161
			Standing	.044	.048	-.050	.139
	Bar	4 pixels	Seating	.244	.048	.150	.339
			Standing	.111	.048	.017	.205
		6 pixels	Seating	.091	.049	-.005	.186
			Standing	.044	.048	-.050	.139
		10 pixels	Seating	.044	.048	-.050	.139
			Standing	.023	.049	-.073	.118

Post Hoc Tests

Chart_OrientationN

Multiple Comparisons

Dependent Variable:Error

	(I) Chart_ OrientationN	(J) Chart_ OrientationN	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Bonferroni	Down	Up	-.0856*	.02002	.000	-.1385	-.0327
		OA (Ref-out)	-.0481	.01979	.091	-.1003	.0042
		OA (Ref-in)	-.0397	.01976	.269	-.0918	.0125
	Up	Down	.0856*	.02002	.000	.0327	.1385
		OA (Ref-out)	.0375	.01999	.363	-.0152	.0903
		OA (Ref-in)	.0460	.01995	.128	-.0067	.0986
	OA (Ref-out)	Down	.0481	.01979	.091	-.0042	.1003

Based on observed means.
The error term is Mean Square(Error) = .104.

*. The mean difference is significant at the .05 level.

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Multiple Comparisons

Dependent Variable:Error

	(I) Chart_Orientation N	(J) Chart_Orientation N	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Bonferroni	OA (Ref-out)	Up	-.0375	.01999	.363	-.0903	.0152
		OA (Ref-in)	.0084	.01972	1.000	-.0437	.0605
	OA (Ref-in)	Down	.0397	.01976	.269	-.0125	.0918
		Up	-.0460	.01995	.128	-.0986	.0067
		OA (Ref-out)	-.0084	.01972	1.000	-.0605	.0437
Tamhane	Down	Up	-.0856*	.02048	.000	-.1396	-.0316
		OA (Ref-out)	-.0481	.01891	.065	-.0979	.0018
		OA (Ref-in)	-.0397	.01856	.181	-.0886	.0093
	Up	Down	.0856*	.02048	.000	.0316	.1396
		OA (Ref-out)	.0375	.02212	.432	-.0208	.0958
		OA (Ref-in)	.0460	.02181	.195	-.0116	.1035
	OA (Ref-out)	Down	.0481	.01891	.065	-.0018	.0979
		Up	-.0375	.02212	.432	-.0958	.0208
		OA (Ref-in)	.0084	.02035	.999	-.0452	.0621
	OA (Ref-in)	Down	.0397	.01856	.181	-.0093	.0886
		Up	-.0460	.02181	.195	-.1035	.0116
		OA (Ref-out)	-.0084	.02035	.999	-.0621	.0452

Based on observed means.
The error term is Mean Square(Error) = .104.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

Different_In_Value

Multiple Comparisons

Dependent Variable:Error

	(I) Different_In_Value	(J) Different_In_Value	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Bonferroni	4 pixels	6 pixels	.0926*	.01727	.000	.0512	.1340
		10 pixels	.1337*	.01725	.000	.0924	.1750
	6 pixels	4 pixels	-.0926*	.01727	.000	-.1340	-.0512
		10 pixels	.0411*	.01710	.049	.0001	.0821
	10 pixels	4 pixels	-.1337*	.01725	.000	-.1750	-.0924
		6 pixels	-.0411*	.01710	.049	-.0821	.0000
Tamhane	4 pixels	6 pixels	.0926*	.01931	.000	.0465	.1388
		10 pixels	.1337*	.01803	.000	.0906	.1768

Based on observed means.
The error term is Mean Square(Error) = .104.

*. The mean difference is significant at the .05 level.

Multiple Comparisons

Dependent Variable:Error

	(I) Different _In_ Value	(J) Different _In_ Value	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Tamhane	6 pixels	4 pixels	-.0926*	.01931	.000	-.1388	-.0465
		10 pixels	.0411*	.01507	.019	.0050	.0771
	10 pixels	4 pixels	-.1337*	.01803	.000	-.1768	-.0906
		6 pixels	-.0411*	.01507	.019	-.0771	-.0050

Based on observed means.
The error term is Mean Square(Error) = .104.

*. The mean difference is significant at the .05 level.

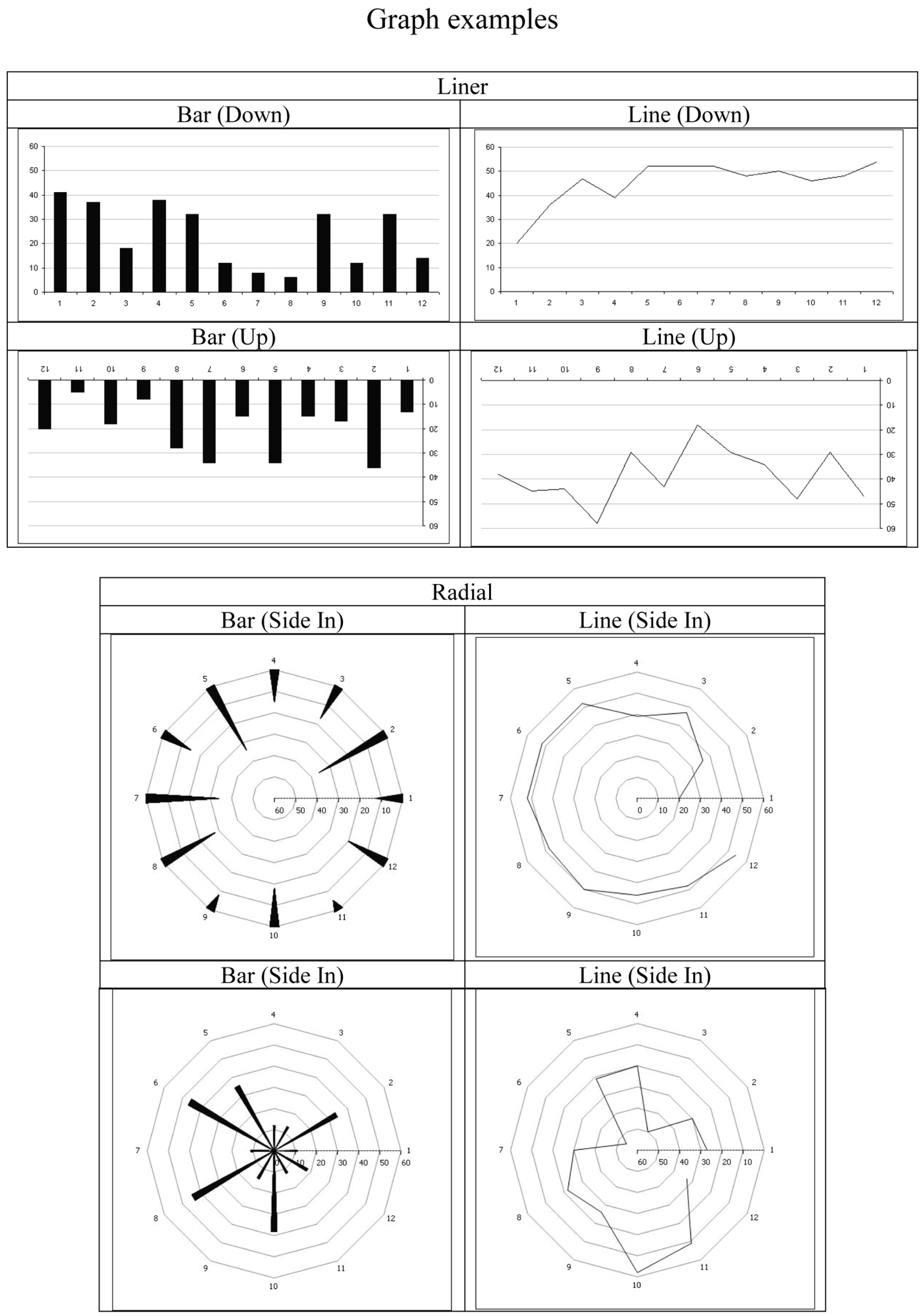

Figure 40: Users have presented with examples of different graph and get tutorial on how to read OA-graph before they do the practise session in experiment 2.

Rate each orientation based on your preference for each. Circle your answer.

	Down	Up	Radial (Side Out)	Right (Side In)
(not preferred) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(preferred) 5	5	5	5	5

Rate each orientation based on your perception of how fast you performed the task. Circle your answer.

	Down	Up	Radial (Side Out)	Right (Side In)
(slowest) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(fastest) 5	5	5	5	5

Rate each orientation based on how difficult you feel it was. Circle your answer.

	Down	Up	Radial (Side Out)	Right (Side In)
(very difficult) 1	1	1	1	1
2	2	2	2	2
(neutral) 3	3	3	3	3
4	4	4	4	4
(easiest) 5	5	5	5	5

Rate graph types based on your preference how difficult you feel they were for all four orientations. Circle your answer.

	Bar (Liner)	Line (liner)	Bar (Side out)	Line (Side out)	Bar (Side in)	Line (Side In)
(not preferred) 1	1	1	1	1	1	1
2	2	2	2	2	2	2
(neutral) 3	3	3	3	3	3	3
4	4	4	4	4	4	4
(preferred) 5	5	5	5	5	5	5

Figure 41: Second set of questions of the post study questionnaire for experiment 1.

Frequencies of user preference for each orientation

Statistics

		0 degree	180 degree	OA-Ref out	OA-Ref in
N	Valid	30	30	30	30
	Missing	0	0	0	0
	Mean	4.50	2.30	2.47	2.87
	Median	5.00	2.00	2.00	3.00
	Mode	5	3	2	2
	Std. Deviation	.731	.837	1.137	1.224

Frequency Table

0 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	4	13.3	13.3	13.3
	4	7	23.3	23.3	36.7
	5	19	63.3	63.3	100.0
	Total	30	100.0	100.0	

180 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	6	20.0	20.0	20.0
	2	10	33.3	33.3	53.3
	3	13	43.3	43.3	96.7
	4	1	3.3	3.3	100.0
	Total	30	100.0	100.0	

OA-Ref out

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	7	23.3	23.3	23.3
	2	9	30.0	30.0	53.3
	3	8	26.7	26.7	80.0
	4	5	16.7	16.7	96.7
	5	1	3.3	3.3	100.0
	Total	30	100.0	100.0	

OA-Ref in

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	3	10.0	10.0	10.0
	2	11	36.7	36.7	46.7
	3	7	23.3	23.3	70.0
	4	5	16.7	16.7	86.7
	5	4	13.3	13.3	100.0
	Total	30	100.0	100.0	

Frequencies of how fast user performed the task

Statistics

		0 degree	180 degree	OA-Ref out	OA-Ref in
N	Valid	30	30	30	30
	Missing	0	0	0	0
	Mean	4.37	2.47	2.47	2.47
	Median	4.00	2.50	2.50	2.00
	Mode	5	3	3	2
	Std. Deviation	.669	1.008	1.008	1.008

Frequency Table

0 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	3	10.0	10.0	10.0
	4	13	43.3	43.3	53.3
	5	14	46.7	46.7	100.0
	Total	30	100.0	100.0	

180 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	6	20.0	20.0	20.0
	2	9	30.0	30.0	50.0
	3	10	33.3	33.3	83.3
	4	5	16.7	16.7	100.0
	Total	30	100.0	100.0	

OA-Ref out

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	6	20.0	20.0	20.0
	2	9	30.0	30.0	50.0
	3	10	33.3	33.3	83.3
	4	5	16.7	16.7	100.0
	Total	30	100.0	100.0	

OA-Ref in

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	16.7	16.7	16.7
	2	11	36.7	36.7	53.3
	3	10	33.3	33.3	86.7
	4	3	10.0	10.0	96.7
	5	1	3.3	3.3	100.0
	Total	30	100.0	100.0	

Frequencies of how diffecult the tasks were for user in each orientation

Statistics

		0 degree	180 degree	OA-Ref out	OA-Ref in
N	Valid	30	30	30	30
	Missing	0	0	0	0
	Mean	4.40	2.53	2.40	2.77
	Median	5.00	2.00	3.00	3.00
	Mode	5	2	3	3
	Std. Deviation	.724	1.042	.894	.935

Frequency Table

0 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3	4	13.3	13.3	13.3
	4	10	33.3	33.3	46.7
	5	16	53.3	53.3	100.0
	Total	30	100.0	100.0	

180 degree

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	16.7	16.7	16.7
	2	11	36.7	36.7	53.3
	3	7	23.3	23.3	76.7
	4	7	23.3	23.3	100.0
	Total	30	100.0	100.0	

OA-Ref out

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	6	20.0	20.0	20.0
	2	8	26.7	26.7	46.7
	3	14	46.7	46.7	93.3
	4	2	6.7	6.7	100.0
	Total	30	100.0	100.0	

OA-Ref in

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	3	10.0	10.0	10.0
	2	8	26.7	26.7	36.7
	3	12	40.0	40.0	76.7
	4	7	23.3	23.3	100.0
	Total	30	100.0	100.0	

Frequencies of users preference for type of chart for all orientation

Statistics

		Bar-Liner	Line-Liner	Bar-OA-Ref out	Line-OA-Ref out	Bar-OA-Ref in	Line-OA-Ref in
N	Valid	30	30	30	30	30	30
	Missing	0	0	0	0	0	0
	Mean	3.47	3.17	3.13	2.70	3.53	3.57
	Median	3.50	3.00	3.00	3.00	4.00	4.00
	Mode	3	3[a]	3	1	4	4
	Std. Deviation	1.196	1.416	1.074	1.368	.900	.858

a. Multiple modes exist. The smallest value is shown

Frequency Table

Bar-Liner

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2	6.7	6.7	6.7
	2	4	13.3	13.3	20.0
	3	9	30.0	30.0	50.0
	4	8	26.7	26.7	76.7
	5	7	23.3	23.3	100.0
	Total	30	100.0	100.0	

Line-Liner

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	5	16.7	16.7	16.7
	2	5	16.7	16.7	33.3
	3	7	23.3	23.3	56.7
	4	6	20.0	20.0	76.7
	5	7	23.3	23.3	100.0
	Total	30	100.0	100.0	

Bar-OA-Ref out

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	2	6.7	6.7	6.7
	2	5	16.7	16.7	23.3
	3	14	46.7	46.7	70.0
	4	5	16.7	16.7	86.7
	5	4	13.3	13.3	100.0
	Total	30	100.0	100.0	

Line-OA-Ref out

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	8	26.7	26.7	26.7
	2	6	20.0	20.0	46.7
	3	6	20.0	20.0	66.7
	4	7	23.3	23.3	90.0
	5	3	10.0	10.0	100.0
	Total	30	100.0	100.0	

Bar-OA-Ref in

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	4	13.3	13.3	13.3
	3	10	33.3	33.3	46.7
	4	12	40.0	40.0	86.7
	5	4	13.3	13.3	100.0
	Total	30	100.0	100.0	

Line-OA-Ref in

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	3	10.0	10.0	10.0
	3	11	36.7	36.7	46.7
	4	12	40.0	40.0	86.7
	5	4	13.3	13.3	100.0
	Total	30	100.0	100.0	