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The effects of x-axis rotation on data estimation accuracy

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The Effects of X-Axis Rotation on Data Estimation Accuracy

An Honors Program Project Presented to
the Faculty of the Undergraduate
College of Health and Behavioral Studies
James Madison University

by Catherine Elizabeth Mathers

May 2015

Accepted by the faculty of the Department of Psychology, James Madison University, in partial fulfillment of the requirements for the Honors Program.

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PUBLIC PRESENTATION

This work is accepted for presentation, in part or in full, at JMU's Honors Symposium on April 24th, 2015.

Dedication

This work is dedicated to James, Carla, and Cara Mathers. Thank you.

Table of Contents

List of Figures	4
Abstract	6
Introduction	7
Methods	13
Results	15
Discussion	20
Appendix	25
References	39

List of Figures

Figures

1a	2D bar graph with labels, axes, and major horizontal gridlines.	28
1b	2D line graph with labels, axes, and obstruction and without major horizontal gridlines.	29
1c	2D bar graph with labels and major horizontal gridlines and without axes.	29
1d	2D bar graph with labels and axes and without major horizontal gridlines.	30
2a	Example of rotation variable.	30
2b	Example of gridlines variable.	31
2c	Example of position variable.	31
3	Interaction of graph type, rotation, and gridlines for total fixation data.	32
4	Interaction of graph type, rotation, and position for total fixation data.	32
5	Interaction of graph type, gridlines, and position for total fixation data.	33
6	Interaction of rotation, gridlines, and position for total fixation data.	33
7	Interaction of graph type, rotation, and gridlines for function fixation data.	34
8	Interaction of graph type, rotation, and position for function fixation data.	34
9	Interaction of graph type, gridlines, and position for function fixation data.	35
10	Interaction of rotation, gridlines, and position for function fixation data.	35
11	Interaction of graph type, rotation, and position for value fixation data.	36
12	Interaction of rotation, gridlines, and position for value fixation data.	36
13	Interaction of graph type, gridlines, and position for value fixation data.	37
14	Interaction of rotation, gridlines, and position for value fixation data.	37
15	Interaction of graph type, rotation, and position for total time data.	38
16	Interaction of graph type, rotation, and gridlines for accuracy data.	38
17	Interaction of graph type, rotation, and position for accuracy data.	39
18	Interaction of rotation, gridlines, and position for accuracy data.	39

Tables

1	Total Fixation Main Effects and Interactions	26
2	Function Fixation Main Effects and Interactions	26
3	Value Fixations for Main Effects and Interactions	27
4	Total Time Main Effects and Interactions	27
5	Accuracy Main Effects and Interactions	28

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Abstract

Researchers, pollsters, marketers, and others use graphical displays to reduce the need for wordy, and often unclear, descriptions of their findings. Numerous studies have attempted to determine important graphical attributes that aid readers' graphical perception. For example, does three-dimensionality (3D) of a graph help readers to accurately assess the graph's data? The present study is the first to use eye movement data to quantify how 3D graphs, graph type, the use of gridlines, and data positioning affected readers' perception and accuracy. Participants viewed 24 different graphs while their eye movements were recorded. Time, fixation, and accuracy were recorded for each graph and for the function, value, and position of each graph. Results showed significant effects of all variables such that performance was worse for: line graphs, 3D graphs, graphs without gridlines, and data positions further from the vertical axis. All variables also interacted. Implications for the graphical representation of quantitative information is discussed.

Introduction

Graphs are a convenient way to present data. They are used to display facts to audiences with a range of aptitudes and are present in documents from the Sunday paper to academic journals. They meet the need of visually detailing information in an appropriate and accurate manner (e.g. Hojnoski, Caskie, Gischlar, Key, Barry, & Hughes, 2009; Shen, Carswell, Santhanam & Bailey, 2012). For visual learners, graphs are necessary for understanding the subject studied. They combine pages of data into one picture that helps to reveal trends and patterns. When it comes to using graphs, two widely used types are the bar graph and the line graph (See Figures 1a & 1b). The visuals in these two types are simple enough for teachers to use in the classroom but detailed enough for medical professionals (Agostinelli et al., 2013; Hojnoski et al., 2009). Both are used for defining relative or absolute amounts; bar graphs typically represent categorical data and line graphs represent continuous data or data over a period of time (Gillan et al., 1998).

Fittingly for the medical and academic audiences who often use statistical displays (Agostinelli et al., 2013; Hojnoski et al., 2009), graphs usually depict basic statistical calculations like frequencies and arithmetic means. Variability is often depicted as the standard error of the mean (SEM) or standard deviation. These calculations are represented by graph elements that show values for an independent (manipulated) or dependent (measured) variable, such as the height of bars in a bar graph; these elements are indicators (Gillan et al., 1998).

Besides graph type and indicators, there are other attributes to graphs that are important for graphical perception. One is the standard axis. It is a line, either horizontal (the 'x' - axis) or vertical (the 'y' - axis) that starts at the bottom left of the graph and extends either upwards or rightwards (See Figures 1c & 1d). The x axis usually shows the scale for the independent

variable and the y axis the scale for the dependent variable. The scale is the domain and range of the axes segmented into equal intervals. The scale must always be greater than or equal to the maximum data point; most scales start at zero, but this is a more of a guideline than a rule.

Labels are used to clarify which variables belong on what axis or, if there are multiple components of a variable, what those components are. Labels are variable names, variables' units of measurement, or both (Gillan et al., 1998). Often data interference occurs but is only an issue if it affects the target indicator, for example the height of the bar graph in question. An obstruction, one example of data interference, is an interrupted visual line to the y-axis from one point by another.

Two dimensional (2D) graphs are determined by the presence of an x and y dimension corresponding to the graph's width and height, respectively. Adding a 'z' dimension – depth – takes a graph from 2D to three dimensional (3D). The z dimension is created by manipulation of a graph's rotation; this is the skew of the graph on the x-axis. Gridlines are extensions from each scale point on the axes and are so named because they form a grid pattern on a graph's background (See Figure 1a).

Creating a graph is half of graphical perception. Interpreting whether the participant perceives it accurately is the other half. To determine if the graph shows the data in the right way, its accuracy must be measured. For graph studies, accuracy is how close an estimated target point is from the y axis to the actual value of the target point. It is measured by the standard deviation in studies with multiple trials or by the raw score of subtracting the estimated value from the actual value. Ideally, in studies where participants must answer a question, they will do so as accurately as possible. However, accuracy decreases when participants try to answer as quickly as possible as well. This is known as the speed-accuracy tradeoff.

Accuracy can be measured for any graph attribute, although there is no known research on how gridlines and position affect accuracy in graphs with rotation. Multiple studies have yet to find a significant difference in accuracy between two and three dimensional displays. Fisher, et al. (1997) studied the usefulness, or how well information is relayed to the reader, of 2D or 3D graphs. Participants viewed five types of 2D graphs, including two types of line graphs and a bar graph, and the same graphs in 3D. Participants answered two questions after viewing the graphs, the first on graph content and the second about which graph was used to answer the first question. The dimension with more correct answers was considered more useful and accurate at depicting the data. The researchers did not find a difference in usefulness of the dimensions. Fischer (2000) also examined 2D and 3D graphs and frames, or the outline or border of the graph. Participants viewed an inequality followed by a graphical display of the inequality with either 2D frame + 2D graph, 3D frame + 3D graph, 2D frame + 3D graph, or 3D frame + 2D graph. Participants answered whether the inequality matched the graph. Again, the dimension with more correct responses would be considered superior. However, there was no difference in the graph condition. Finally, Spence (2004) examined 2D and 3D object displays. Participants viewed one dimensional (1D), 2D, and 3D displays of five objects, including boxes, rectangles, and lines. They then divided the object into two equal proportions. The dimension with the higher number of correct divisions would be considered more accurate and the dimension optimal for display use. 1D displays were significantly better than the other two dimensions, but 2D and 3D graphs were not significantly different from each other. In sum, altering rotation to produce a 3D graph does not have an impact on accuracy.

Similar results have also been found for graph type. Hojniski et al (2009) presented teachers with a table, bar graph, line graph, and narrative then tested for user preference and

accuracy. Results showed that line graphs and bar graphs were not different in either basic accuracy (reading of the target value) or interpretive accuracy (analysis of the target value). Spence (1990) found a significant, 1% difference in accuracy for graph type. Participants viewed cylinders, boxes, bars, lines, disks, or pies in 1D, 2D, or 3D. The participants had to divide the graph display into equal halves. Bars and pies had a standard error of less than 3% and boxes cylinders, and lines had an error between 3-4% (Spence 1990). Because studies show manipulation of graph type may or may not affect accuracy, this attribute must be measured further.

Very little research has investigated the role of eye movements on graph perception. Visual information is voluntarily taken in through saccades, and these affect the perception of the graphs (Ashcraft & Radvansky, 2009; Zhang et al., 2011). Saccades are fast, jerky, ballistic eye movements that alter the point of fixation. They are rapidly changing and voluntary in nature (Purves et al., 2001). Some studies involving the eye tracker study display dimensionality or graph type, never both simultaneously (Chelnokova & Laeng, 2011; Huestegge & Phillip, 2011). However, research has been conducted using an eye tracker that shows graphs constructed in conjunction with design criteria have an advantage in accuracy and task completion time (Renshaw, Finlay, Ward & Tyfa, 2003). Most research done on eye movements and using an eye tracker concerns visual attention (e.g. DeAngelus & Pelz, 2009; O'Sullivan, 2005). The studies show that eye movements can measure visual attention and center on prominent elements, inferring that eye movements can reveal the main elements of graphs. However, the distinction between prominent elements and relevant elements has not been addressed. For an element to be relevant, it must be important to the task for which the graph is used; the highest bar in a bar graph is prominent, but if the task is to determine the shortest bar then the highest bar is

irrelevant. Prominent but irrelevant elements are distractor elements and may take away from the reader's understanding of the graph. Thus, a third dimension on a graph may present distractor elements.

Wexler and Ouarti (2008) determined that the direction of saccades is affected by 3D scenes. Participants monocularly or binocularly viewed a grid, texture gradient, or dot texture (the control) in a circular window. The direction of saccades (voluntary movement of the eyes from one point of fixation to another) determined whether the participant viewed the stimuli as two or three dimensional; as the tilt or depth of the stimuli increases, so does the dimensionality. All conditions except for the control were statistically significant. This suggests that using a 3D display will have a lasting and different impact on graph perception in comparison to a 2D display. Korner (2011) found that visual searches for specific information are not affected by graph properties. Participants viewed hierarchal graphs (nodes connected by lines) and measured the fixations and eye movements using an eye tracker. Their first experiment and second experiments tested visual search and graph comprehension, respectively; their third experiment combined the purposes of the first two. Visual properties of the graphs were manipulated, such as whether the nodes were crossed or not. The first experiment had multiple trials in which lines were either crossed or uncrossed; targets were found faster in the second search trial than the first trial – a significant difference, but this was due to familiarity effects and not obstruction of the nodes.

Korner (2011) used a comprehension task with a graph search task to measure accuracy, but he was not concerned with bar or line graphs or other graph attributes. This study is one of many that are concerned with only one attribute of graphs (Barfield & Robless, 1989; Berg & Ilpo, 2012; Fischer, 2000; Shen, 2012). Previous research has not investigated deeply accuracy

effects of gridlines on dimension, graph type, or position. However, these can be assessed using eye movements. Graphs studying dimension focus solely on dimension, occasionally investigating graph type but neglecting gridlines and obstruction and vice versa. Because graphs consist of more than one major attribute, the present study looks at graphs as a whole. We studied position, gridlines, graph type, dimension and their relation to each other. We measured the response time, or the time from presentation of stimuli to participant's reaction to stimuli, and response accuracy by eye movements.

We predicted that (1) 2D graphs would yield faster and more accurate answers than their 3D counterparts, especially as the distance in x-axis rotation increased. We predicted that (2) gridlines would increase response accuracy in both dimension. We also predicted (3) an increase in response time and decrease in response accuracy for the target indicator with greater obstruction. Finally, we predicted (4) a difference in response accuracy and time for graph type in the 3D graph condition.

Methods

Participants

Fifty five undergraduate students (age: $M = 19.61$, men = 11, women = 44) were recruited from the participant pool of James Madison University's Psychology Program. Five participants were excluded due to software malfunction for a total of 50 participants. Participants received class credit for partaking in the study.

Design

Our design used a 2 x 2 x 2 x 3 within-subjects factorial design with a Greenhouse-Geisser correction. Factors included graph type (bar v line), rotation (2D v 20 degrees v 40 degrees; see Figure 2a), gridlines (major v none; see Figure 2b), and x-axis location (second position or seventh position on the x axis; see Figure 2c). Areas of interest (AOIs) were marked at the position of the data on the x-axis, value of the data on the y-axis, and the function of the data.

Materials/Apparatus

Participants completed a study on the Tobii T60 eye-tracker with a 17 inch monitor. The Tobii eye-tracker allows for full freedom of head movement and binocular viewing at 57 cm. Participants viewed 24 graphs that were either bar or line; rotated zero degrees (2D), 20 degrees, or 40 degrees; had major gridlines or no gridlines; and asked about either position two or position seven. Graphs were made on Microsoft Excel and enlarged on Microsoft Paint. All graphs when viewed on the screen were 30.42cm x 18.41cm. The scale of the y axis was zero to 100, and target values were between 20 and 80.

Procedure

After participants provided informed consent, the experimenter explained how to perform the tasks and how the eye tracker works. The participant then completed a training session, during which the participant answered practice questions after viewing six graphs containing all of the study's factors. Before beginning the training, the eye tracker calibrated each participant. After the training, the participant began the experiment. The participant gave answers orally; the experimenter sat behind the participant and recorded the responses. Halfway through the experiment, the participant had a minute break. After completing the experiment, the participant was debriefed and dismissed.

Results

Total Fixations

Total fixations represents the total number of fixations a participant had on a graph. There were many significant main factor effects and factor interactions on total fixations; their statistics can be found in Table 1. The main effect data showed that more fixations were found with (1) line graphs, (2) 3D graphs, (3) graphs with no gridlines, and (4) when participants had to identify target values corresponding to Position 7.

From the long list of significant interactions, we identified a number of interesting ones. There was a significant interaction of graph type and rotation and gridlines (See Figure 3). For all bar graphs, there were more fixations on graphs without gridlines than graphs with gridlines. For line graphs with 0° and 20° , there were more fixations on graphs without gridlines than graphs with gridlines. Line graphs with 40° had fewer fixations on graphs without gridlines than graphs with gridlines. There was a significant interaction of graph type and rotation and position. (See Figure 4). For all bar graphs, there were more fixations for Position 7 than Position 2. For all line graphs, there were more fixations for Position 7 than Position 2.

There was a significant interaction of graph type, gridlines, and position (See Figure 5). For bar graphs with gridlines or without gridlines, there were more fixations for Position 7 than Position 2. For line graphs with gridlines or without gridlines, there were more fixations for position seven than position two. There was a significant interaction of rotation, gridlines, and position (See Figure 6). For 0° rotation with gridlines or without gridlines, there were more fixations for Position 7 than Position 2. For 20° rotation with gridlines or without gridlines, there were more fixations for Position 2 than Position 7. For 40° rotation with gridlines or without gridlines, there were more fixations for Position 2 than Position 7.

Function Fixations

The function is the visual representation of the data within the x- and y- axes. Function fixations are the number of times the participant fixated on the function (the bars/ lines) within the graphs themselves. There were many significant main factor effects and factor interactions on function fixations; their statistics can be found in Table 2. The main effect data showed that more function fixations were found with (a) graphs with no gridlines and (b) when participants had to identify target values corresponding to Position 7.

We identified a number of interesting interactions. There was a significant interaction of graph type, rotation, and gridlines (See Figure 7). For all bar graphs, there were more function fixations for graphs without gridlines than graphs with gridlines. For line graphs with 0° and 20° rotations, there were more function fixations for graphs without gridlines than graphs with gridlines. For line graphs with 40° rotation, there were fewer fixations for graphs without gridlines than graphs with gridlines. There was a significant interaction of graph type and rotation and position (See Figure 8). For bar graphs with 0° and 40° rotations, there were more function fixations for Position 7 than Position 2. For bar graphs with 20° rotation, there were fewer function fixations for Position 7 than Position 2. For line graphs with 0° and 20° rotations, there were more function fixations for Position 7 than Position 2. For line graphs with 40° rotation, there were fewer function fixations for Position 7 than Position 2.

There was a significant interaction of graph type and gridlines and position (See Figure 9). For bar graphs with gridlines, there were less function fixations for Position 7 than Position 2. For bar graphs without gridlines, there were more function fixations for Position 7 than Position 2. For line graphs with gridlines or without gridlines, there were more function fixations for Position 7 than Position 2. There was a significant interaction of rotation and gridlines and

position (See Figure 10). For 0^0 rotation with gridlines, there were fewer function fixations for Position 7 than Position 2. For 0^0 rotation without gridlines, there were more function fixations for Position 7 than Position 2. For 20^0 rotation with gridlines, there were less function fixations for Position 7 than Position 2. For 20^0 rotation without gridlines, there were more function fixations for Position 7 than Position 2. For 40^0 rotation with gridlines, there were more function fixations for Position 7 than Position 2. For 40^0 rotation without gridlines, there were fewer function fixations for Position 7 than Position 2.

Value Fixations

The value is the height of the target function. Value fixations are the number of times the participant fixated on the y-axis height corresponding to the function. There were many significant main factor effects and factor interactions on value fixations; their statistics can be found in Table 3. The main effect data showed that more value fixations were found with (1) bar graphs, (2) 2D graphs, (3) graphs with no gridlines, and (4) when participants had to identify target values corresponding to Position 7. All but (1) and (2) were expected.

We identified a number of interesting interactions. There was a significant interaction of graph type and rotation and position (See Figure 11). For bar graphs with 0^0 rotation, there were fewer value fixations for Position 7 than Position 2. For bar graphs with 20^0 and 40^0 rotations, there were more value fixations for Position 7 than Position 2. For line graphs with 0^0 and 40^0 rotations, there were more value fixations for Position 7 than Position 2. For line graphs with 20^0 rotation, there were fewer value fixations for Position 7 than Position 2. There was a significant interaction of rotation and gridlines and position (See Figure 12). For 0^0 rotation with gridlines, there were fewer value fixations for Position 7 than Position 2. For 0^0 rotation without gridlines, there were fewer value fixations for position seven than two. For 20^0 rotation with gridlines,

there were more value fixations for Position 7 than Position 2. For 20⁰ rotation without gridlines, there were fewer value fixations for Position 7 than Position 2. For 40⁰ rotation with gridlines, there were more value fixations for Position 7 than Position 2. For 40⁰ rotation without gridlines, there were fewer value fixations for Position 7 than Position 2.

Total Time

Total time represents the total amount of time a participant spent viewing a graph. There were many significant main factor effects and factor interactions on total time; their statistics can be found in Table 4. The main effect data showed that longer viewing times were found with (1) line graphs, (2) 3D graphs, (3) graphs with no gridlines, and (4) when participants had to identify target values corresponding to position seven.

We identified a number of interesting interactions. There was a significant interaction of graph type and rotation and position (See Figure 13). For all line graphs, more time was spent on position seven than two. For bar graphs with 0⁰ rotation, less time was spent on Position 7 than Position 2. For bar graphs with 20⁰ and 40⁰ rotation, more time was spent on Position 7 than Position 2. There was a significant interaction of graph type and gridlines and position (See Figure 14). For line graphs with gridlines and without gridlines, more time was spent on Position 7 than Position 2. For bar graphs with gridlines or without gridlines, more time was spent on Position 7 than Position 2. There was a significant interaction of rotation and gridlines and position (See Figure 15). For 0⁰ rotation with gridlines and without gridlines, more time was spent on Position 2 than Position 7. For 20⁰ rotation with gridlines or without gridlines, more time was spent on Position 2 than Position 7. For 40⁰ rotation with gridlines or without gridlines, more time was spent on Position 2 than Position 7.

Accuracy

Accuracy was measured by obtaining the absolute difference from the actual value score and the participant's estimate value score; lower scores indicate higher accuracy. There were many significant main factor effects and factor interactions on accuracy; their statistics can be found in Table 5. The main effect data showed that less accuracy was found with (1) 3D graphs, (2) graphs with no gridlines, and (3) when participants had to identify target values corresponding to position seven.

We identified a number of interesting interactions. There was a significant interaction of rotation and gridlines. Accuracy decreases for graphs with gridlines and graphs without gridlines as rotation increases. There was a significant interaction of rotation and position. Accuracy decreases for both Position 2 and Position 7 as rotation increases. There was a significant interaction of graph type and rotation and gridlines (See Figure 16). For line graphs with 0° and 40° rotations, the graphs with gridlines were more accurate than without gridlines. For line graphs with 20° rotation, the graphs with gridlines were less accurate than without gridlines. For all bar graphs, the graphs with gridlines were more accurate than without gridlines. There was a significant interaction of graph type and rotation and position (See Figure 17). For all line graphs, Position 7 estimations were less accurate than Position 2 estimations. For all bar graphs, Position 7 estimations were less accurate than Position 2 estimations.

There was a significant interaction of rotation, gridlines, and position (See Figure 18). For 0° rotation with gridlines or without gridlines, Position 7 estimations were less accurate than Position 2 estimations. For 20° rotation with gridlines, Position 7 estimations were less accurate than Position 7 estimations. For 20° rotation without gridlines, Position 7 estimations were more accurate than Position 2 estimations. For 40° rotation with gridlines or without gridlines, Position 7 estimations were less accurate than Position 2 estimations.

Discussion

The present study examined the effects that multiple graph parts have on readers' perceptions. Specifically, the study gauged the accuracy of data estimations when graph type, rotation, gridlines, and data position are manipulated. We also examined readers' fixations and time spent viewing graphs overall and in several AOIs. Through this we were able to judge where the participants were looking and if they had difficulties analyzing on the graphs. When it comes to total fixations and total time, line graphs and 3D graphs had greater cognitive demands. When examining value fixations, bar graphs and 2D graphs had greater cognitive demands. With accuracy, 3D graphs had greater cognitive demands. Graphs that did not have gridlines and data points further from the y axis had greater cognitive demands across all dependent variables.

Fixations

Our results are in direct contrast to those in Korner (2011), who found that graph properties did not have a systematic effect on graph efficacy and that fixations decreased as visual properties are added to the graph. We believe that this difference is due to the type of graphs Korner (2011) investigated (hierarchical v. bar and line) as well as the graph properties (planarity, slow, and levels v. type, rotation, gridlines, and position). Our findings support research by Renshaw et al. (2003). Both studies found increased total fixations and error (decreased accuracy) for 3D graphs. Renshaw et al. (2003) investigated two types of graphs that contained a couple properties also examined in our study, namely dimension and gridlines.

Time

Our results also agree with those from Fischer (2000), who found that 3D graphs had longer processing times than 2D graphs. This was expected, as the procedure and design of our study was roughly modeled after Fischer's. Our findings agree with Spence (2004), who found

that 3D bars had longer viewing times than 2D bars when both were in compatible frames (2D bars with 2D frames; 3D bars with 3D frames).

Accuracy

As we expected, the 3D graphs were less accurate than the 2D graphs. This result contrasts with Chelnokova and Laeng (2011), who found higher accuracy for 3D images. However, their study concerned facial recognition and not graphical displays. As well, accuracy in our study was determined by a search task, not a recognition task. Our result also contrasts with Hojnoski et. al (2009), who found that line graphs had greater accuracy than bar graphs. We believe this difference is due to the type of questions asked. Hojnoski et. al (2009) used not only value questions like those in our study, but interpretive questions as well. Our findings agree with those from Fischer (1997), who found an increase in accuracy for bar versus line graphs and a trend of increased accuracy for 2D versus 3D graphs.

Gridlines

Our study also contrasts with Gillan et. al (1998) and Renshaw et. al (2003). Both advised against using gridlines, as gridlines increase visual clutter and therefore are cognitively taxing. As we found, though, the presence of gridlines in graphs decreased the cognitive load: Less time, fixations, and error occurred for graphs with gridlines than those without. Gillans et. al (1998), though, is a guide designed to broadly apply to all manner of graphs. Renshaw et al. (2003) did not examine individual properties; 3D graphs were always shown without gridlines and vice versa.

As our study has demonstrated, 3D graphs and line graphs increase both the time viewing and number of eye fixations of the viewer. Although prior research by Renshaw et. al (2003) found that 3D graphs led to more fixations, they did not isolate the dimensionality variable from

other potentially confounding variables. Our study reasonably demonstrates that the extra third dimension significantly increases the number of fixations on a graph, as does using a line graph over a bar graph. A consequence of an increase in eye movements is the possibility of inputting extraneous information, increasing the cognitive load of the viewer. The viewer cannot find the target in the display and thus fixates upon many different targets. More importantly, a viewer using a 3D graph, a line graph, or a combination of both incurs a high cost: visual fatigue. As the eyes move around more to compensate for the increased cognitive difficulty, the muscles may become tired and strained. The viewer may stop processing as much visual information as he or she would if the data were presented in a 2D graph or a bar graph.

Additionally, the increases in fixations and time imply that 3D graphs are less efficient at presenting data. Traditional measures of efficiency are centered on accuracy measurements. However, for us efficiency is equivalent to accuracy and effort. Viewers give less accurate answers when using 3D graphs. If their eyes are fatigued as well, they will not put in full effort. Reduced accuracy and reduced effort consequently mean reduced efficiency. As well, when graphs are less efficient, viewers waste a significant amount of time viewing them. As our study also showed, the less efficient graphs were viewed longer than their more efficient counterparts.

It was also interesting to us that adding gridlines significantly increased the efficiency of graphs. As we found, gridlines were beneficial to the displays; they significantly decreased the number of fixations at graph functions and were one of two variables to do so. This implies that gridlines may be able to decrease the chance of incurring visual fatigue. The importance of using gridlines has been underplayed or nullified. There is a hesitation to using gridlines because they are visually busy and purportedly take away from target or the task of the graph (Renshaw et. al,

2003). We did not find that they were a visual overload; in our study, they were adept at decreasing cognitive demands.

There were several limitations to the study. The study was designed to be brief, but some students may have been bored after viewing 48 graphs and hurried through the experiment without being as accurate as possible. As well, the eye-tracking software would occasionally freeze during the experiment. There may have been other error within the software not so obvious and easily caught.

The present study tested numerous independent and dependent variables, which in addition to providing much data also produced many interactions. Future studies using eye movements for graph research should focus on fewer variables. Our study focused on two different graph types. However, this does not mean that research should be limited to bar and line graphs. The effects of x-axis rotation should also be studied for other graph types as well. Our study also focused on three x-axis rotations that had visually evident differences. It would be interesting to see if rotation has as clear an effect as the one we found if the difference between rotation levels is smaller. Also, we were surprised the function fixations didn't follow the same trend as the total fixations. We are not sure of why there is this difference; it may be because the function of the graph was a specific target and easier to focus upon, as opposed to the entire graph. This should be examined in future studies. The accuracy in our study was the absolute difference between the correct and given responses. Future studies may want to examine if the accuracy is positive or negative. Increased accuracy for the error variable may be produced through more than two replications per graph. However, researchers who increase the number of graphs viewed should be cognizant of fatigue effects. Measures other than AOIs could be utilized to determine efficacy; TOBII also has heat map and cluster capabilities.

In sum, our experiment found that graph attributes do affect viewers' perceptions of data. By utilizing available eye tracking software, we were able to see how increasing the rotation of a graph increased the number of fixations and time spent on it. We found that the presence of gridlines not only affected the accuracy of data estimation but simultaneously decreased the number of eye fixations on the graph. We also found that presenting data in line graphs significantly increased the number of fixations and time, as opposed to when presenting data in bar graphs. As well, our variables significantly affected not only data perception but each other. Lastly, no research like the current study has been conducted; there have not been any studies utilizing eye movements as a method of determining graph efficacy. Research would benefit from replication studies to further add support for our findings.

Appendix

Table 1

Total Fixation Main Effects and Interactions

Variables	df	F	p	η^2_p
Graph type	1, 49	46.528	<.001	.487
Rotation	1.94, 94.91	13.497	<.001	.216
Gridlines	1, 49	33.841	<.001	.409
Position	1, 49	54.38	<.001	.526
Graph type * Gridlines	1, 49	9.579	.003	.164
Rotation * Gridlines	1.96, 95.87	9.232	<.001	.159
Graph type * Rotation * Gridlines	1.89, 92.942	7.075	.001	.126
Graph type and Position	1,49	11.31	.002	.188
Graph type * Rotation * Position	1.98, 96.89	18.18	<.001	.271
Gridlines * Position	1, 49	15.085	<.001	.235
Graph type * Gridlines * Position	1, 49	12.397	.001	.202
Rotation * Gridlines * Position	1.99, 97.63	5.36	.006	.099
Graph type * Rotation * Gridlines * Position	1.89, 92.75	21.47	<.001	.305
<i>Note. $\alpha = .05$</i>				

Table 2

Function Fixation Main Effects and Interactions

Variables	df	F	p	η^2_p
Gridlines	1, 49	4.621	.037	.086
Position	1, 49	7.185	.01	.128
Graph type * Rotation	1.91, 93.62	10.705	<.001	.179
Graph type * Gridlines	1, 49	55.073	<.001	.529
Rotation * Gridlines	1.73, 84.93	17.527	<.001	.263
Graph type * Rotation * Gridlines	1.83, 89.74	8.181	.001	.143
Graph type * Rotation * Position	1.83, 89. 69	11.269	<.001	.187
Gridlines * Position	1, 49	6.664	.013	.12
Graph type * Gridlines * Position	1, 49	30.885	<.001	.387
Rotation * Gridlines * Position	1.82, 89.44	24.088	<.001	.33
Graph type * Rotation * Gridlines * Position	1.74, 85.38	12.703	<.001	.206
<i>Note. $\alpha = .05$</i>				

Table 3

Value Fixations for Main Effects and Interactions

Variables	df	F	p	η^2_p
Graph type	1, 49	34.77	<.001	.415
Rotation	1.99, 97.86	3.999	.021	.075
Gridlines	1, 49	53.916	<.001	.524
Position	1, 49	5.607	.022	.103
Graph type * Rotation	1.69, 82.69	9.244	.001	.159
Graph type * Rotation * Position	1.76, 86.5	11.092	<.001	.185
Gridlines * Position	1, 49	8.251	.006	.144
Rotation * Gridlines * Position	1.89, 92.45	14.181	<.001	.224

Note. $\alpha = .05$

Table 4

Total Time Main Effects and Interactions

Variables	df	F	p	η^2_p
Graph type	1, 49	59.068	<.001	.547
Rotation	1.69, 82.9	35.963	<.001	.423
Gridlines	1, 49	7.338	.009	.13
Position	1, 49	55.718	<.001	.532
Graph type * Gridlines	1, 49	12.307	.001	.197
Rotation * Gridlines	1.96, 93.31	5.972	.004	.109
Graph type * Position	1, 49	23.147	<.001	.305
Rotation * Position	1.97, 96.54	8.731	.002	.121
Graph type * Rotation * Position	1.99, 97.9	22.042	<.001	.223
Gridlines * Position	1, 49	25.905	.007	.141
Graph type * Gridlines * Position	1, 49	13.901	.011	.126
Rotation * Gridlines * Position	1.99, 97.67	6.955	.016	.081

Note. $\alpha = .05$

Table 5

Accuracy Main Effects and Interactions

Variables	df	F	p	η^2_p
Rotation	1.80, 84.77	151.157	<.001	.763
Gridlines	1, 47	69.185	<.001	.595
Position	1, 47	32.390	<.001	.408
Graph type * Rotation	1.97, 92.49	23.458	<.001	.333
Graph type * Gridlines	1, 47	29.804	<.001	.388
Graph type * Rotation * Gridlines	1.70, 79.95	49.744	<.001	.514
Graph type * Position	1, 47	62.055	<.001	.569
Rotation * Position	1.86, 87.6	3.688	.032	.073
Graph type * Rotation* Position	1.87, 88.09	22.192	<.001	.321
Gridlines * Position	1, 47	8.33	.006	.151
Rotation * Gridlines * Position	1.96, 92.01	65.266	<.001	.581
Graph type * Rotation * Gridlines * Position	1.97, 92.53	29.802	<.001	.382

Note. $\alpha = .05$

Figure 1a. 2D bar graph with labels, axes, and major horizontal gridlines.

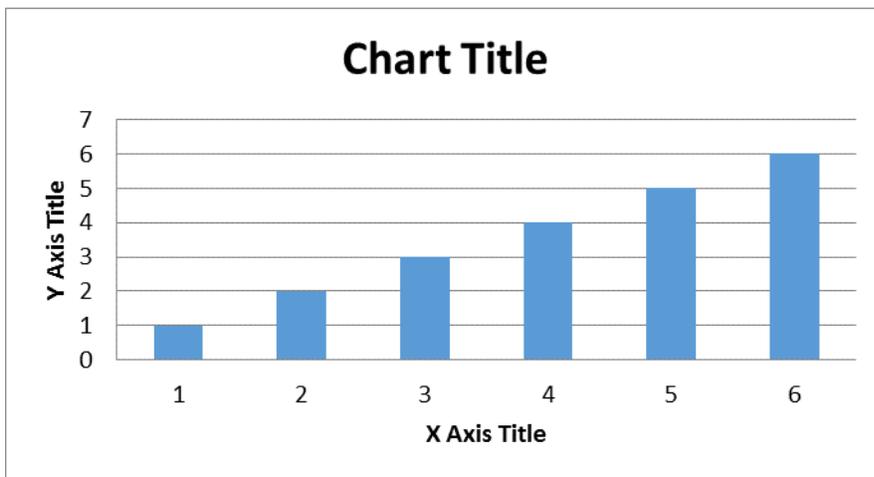


Figure 1b. 2D line graph with labels, axes, and obstruction and without major horizontal gridlines.

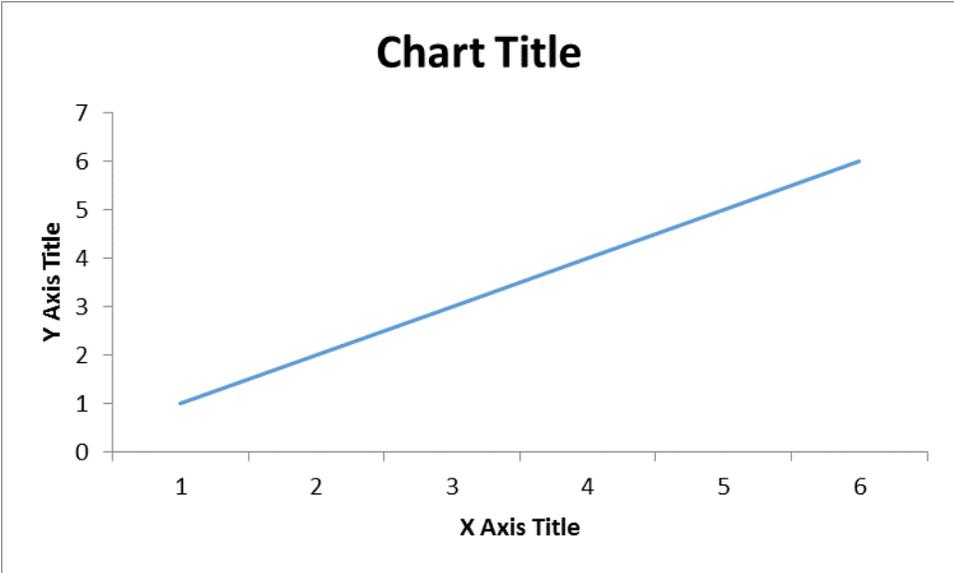


Figure 1c. 2D bar graph with labels and major horizontal gridlines and without axes.

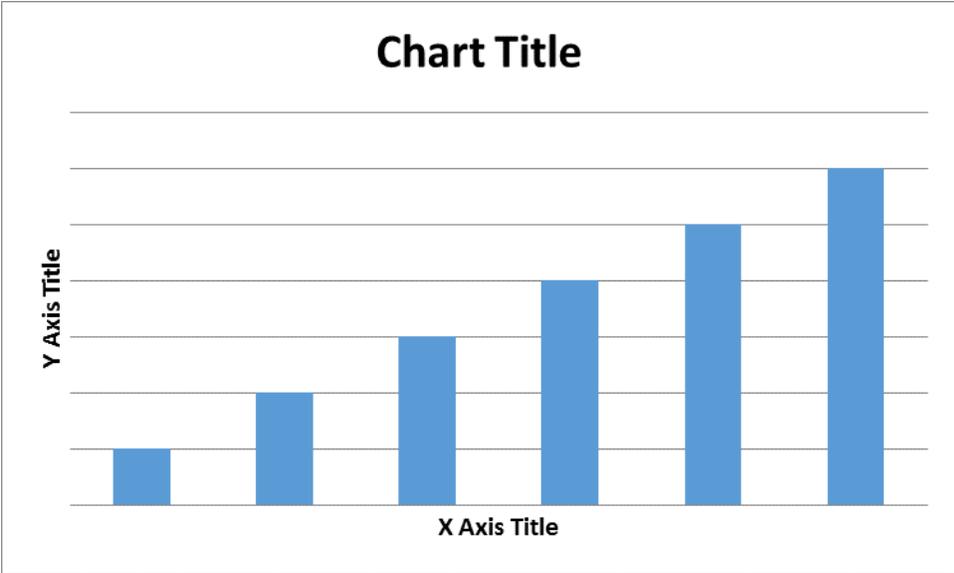


Figure 1d. 2D bar graph with labels and axes and without major horizontal gridlines.

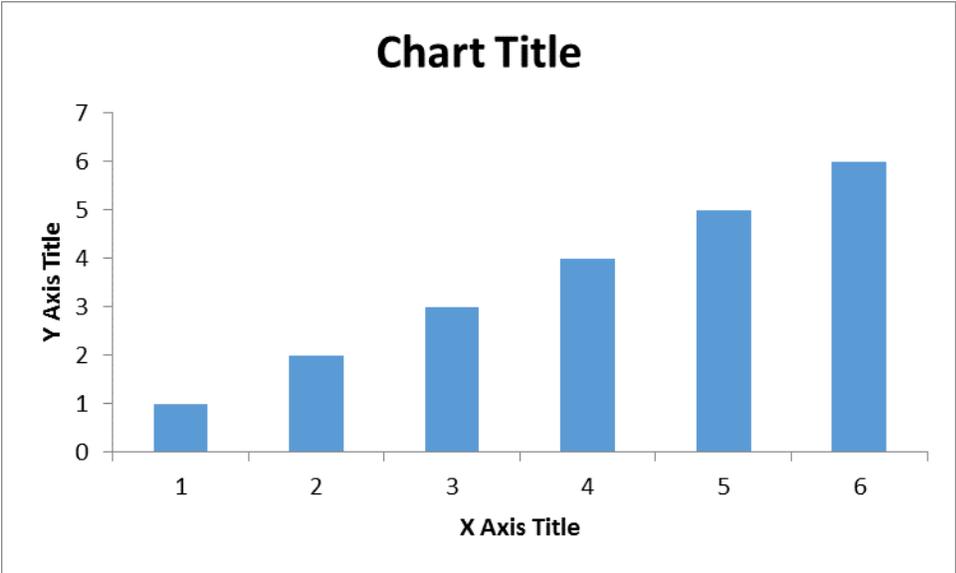


Figure 2a. Example of rotation variable.

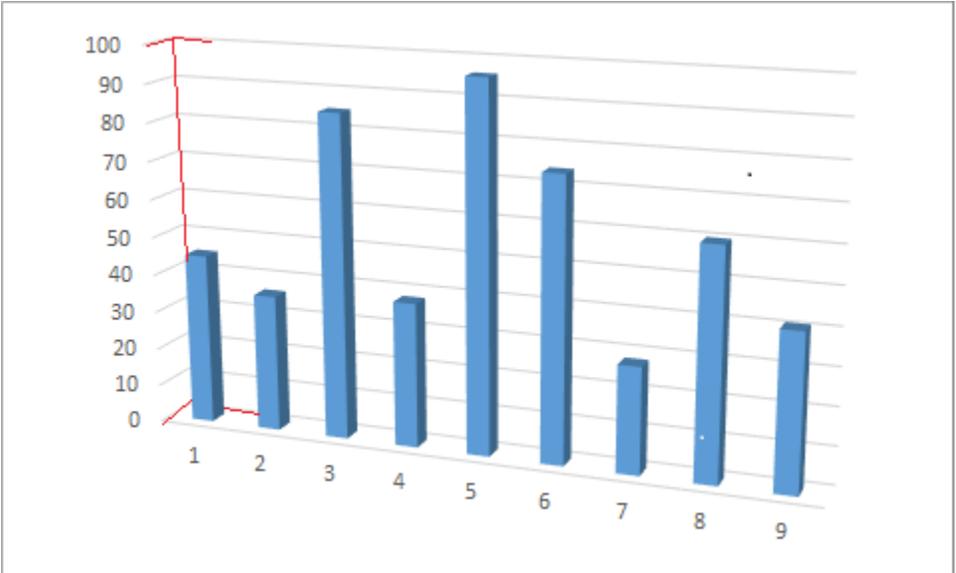


Figure 2b. Example of gridlines variable.

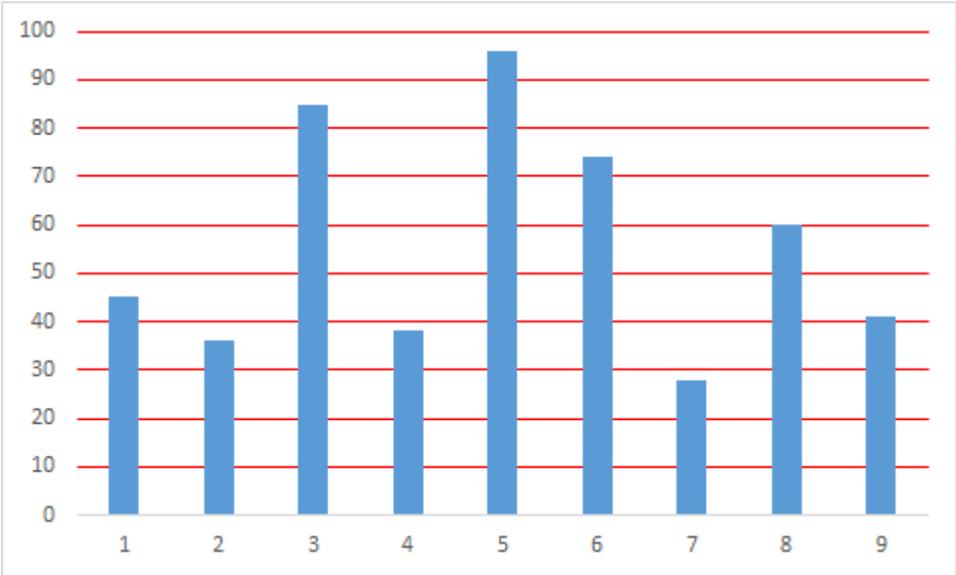


Figure 2c. Example of position variable.

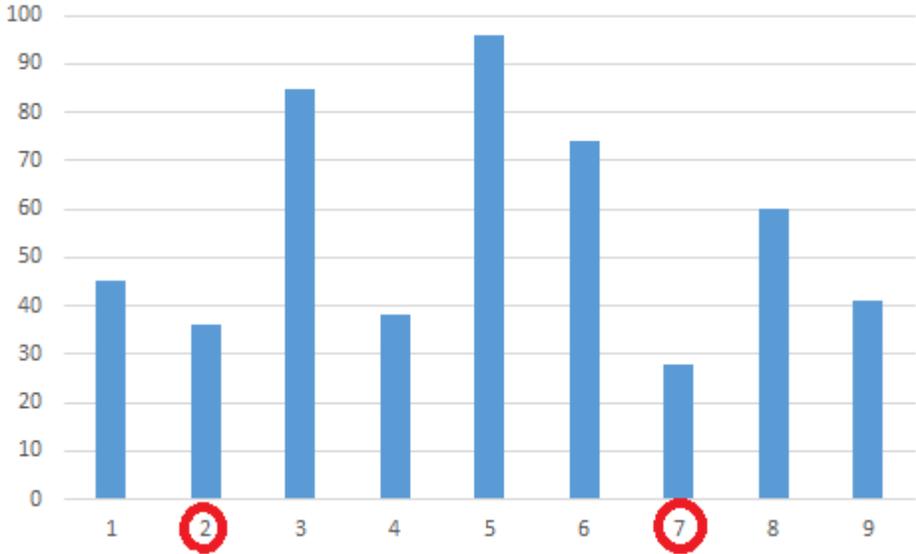


Figure 3. Interaction of graph type, rotation, and gridlines for total fixation data.

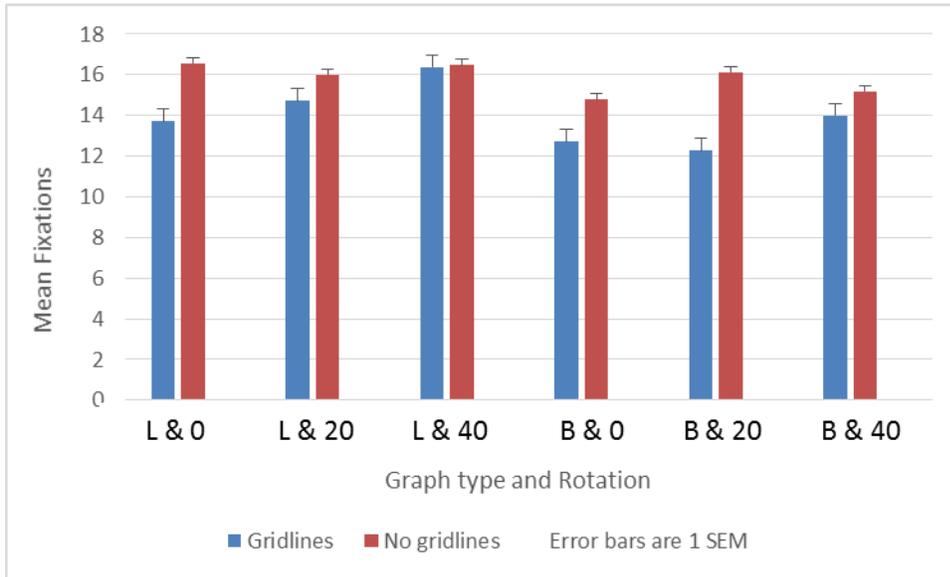


Figure 4. Interaction of graph type, rotation, and position for total fixation data.

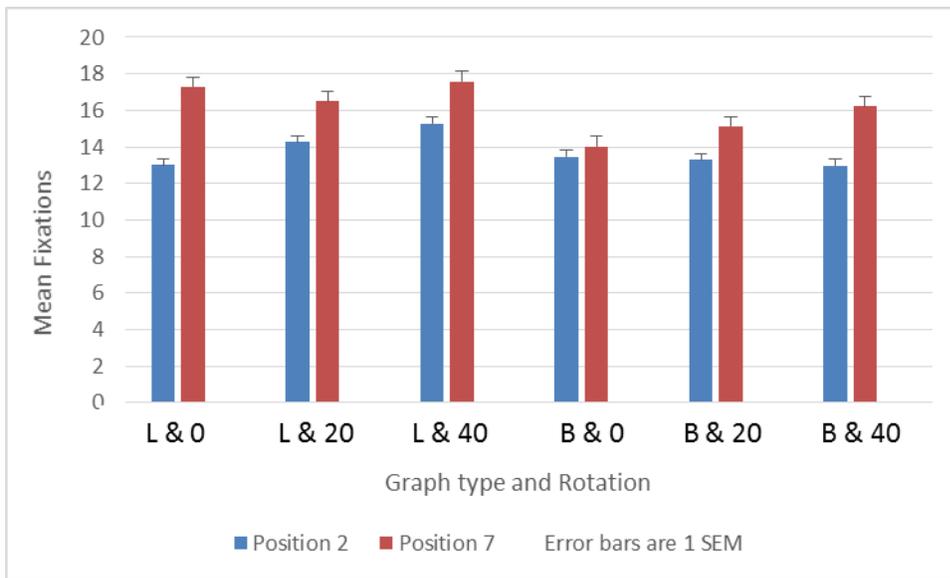


Figure 5. Interaction of graph type, gridlines, and position for total fixation data.

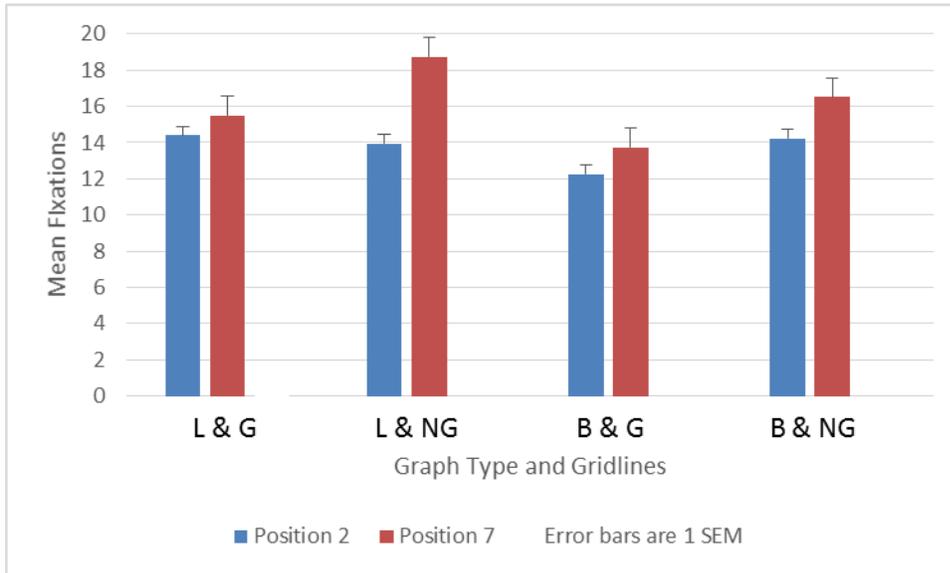


Figure 6. Interaction of rotation, gridlines, and position for total fixation data.

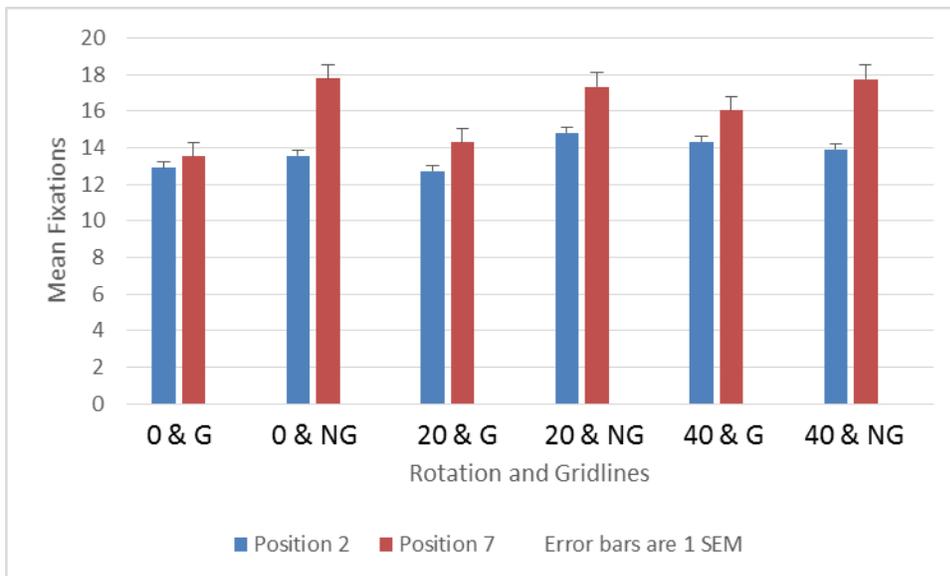


Figure 7. Interaction of graph type, rotation, and gridlines for function fixation data.

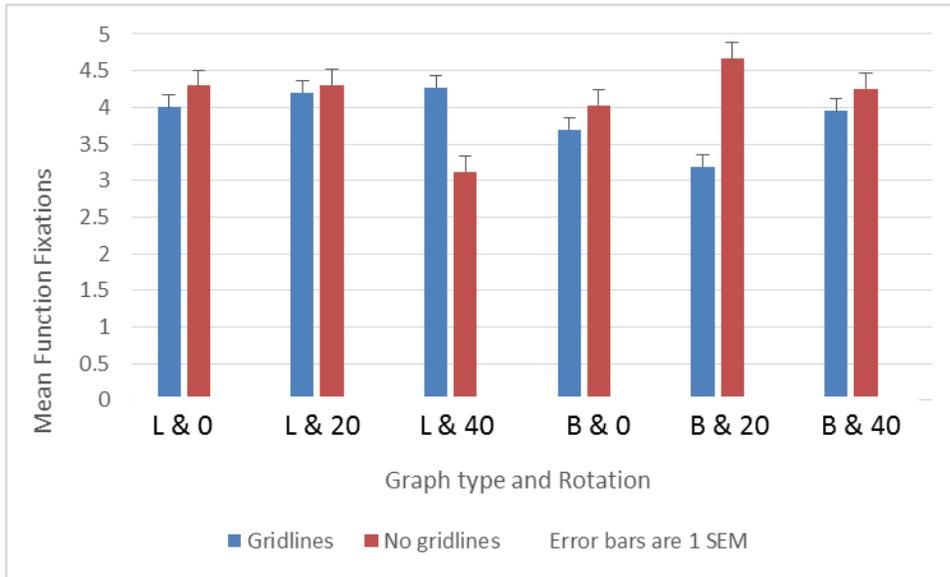


Figure 8. Interaction of graph type, rotation, and position for function fixation data.

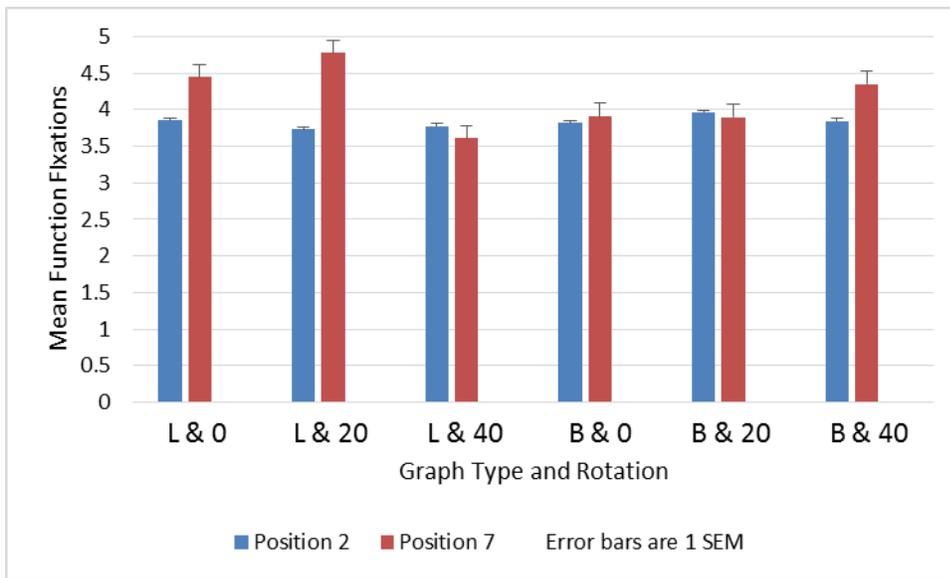


Figure 9. Interaction of graph type, gridlines, and position for function fixation data.

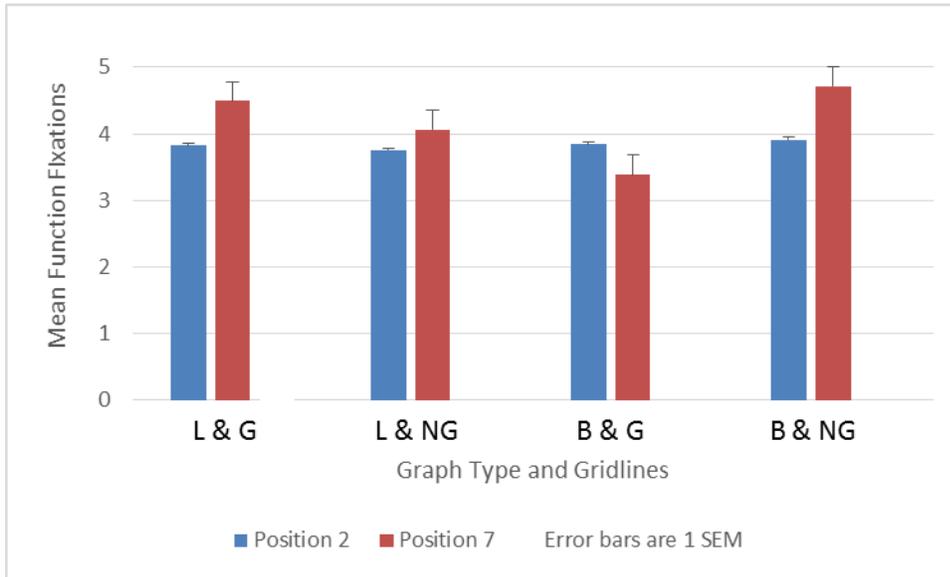


Figure 10. Interaction of rotation, gridlines, and position for function fixation data.

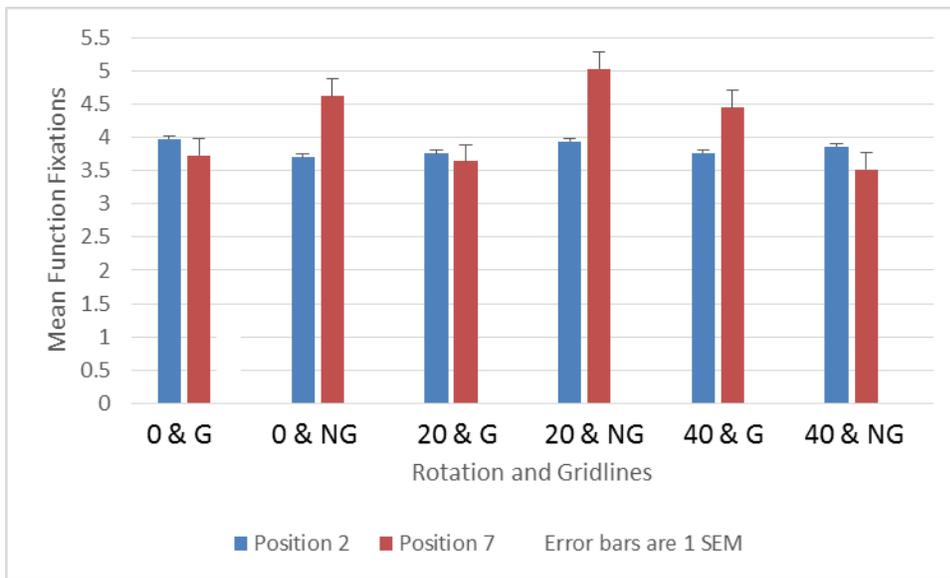


Figure 11. Interaction of graph type, rotation, and position for value fixation data.

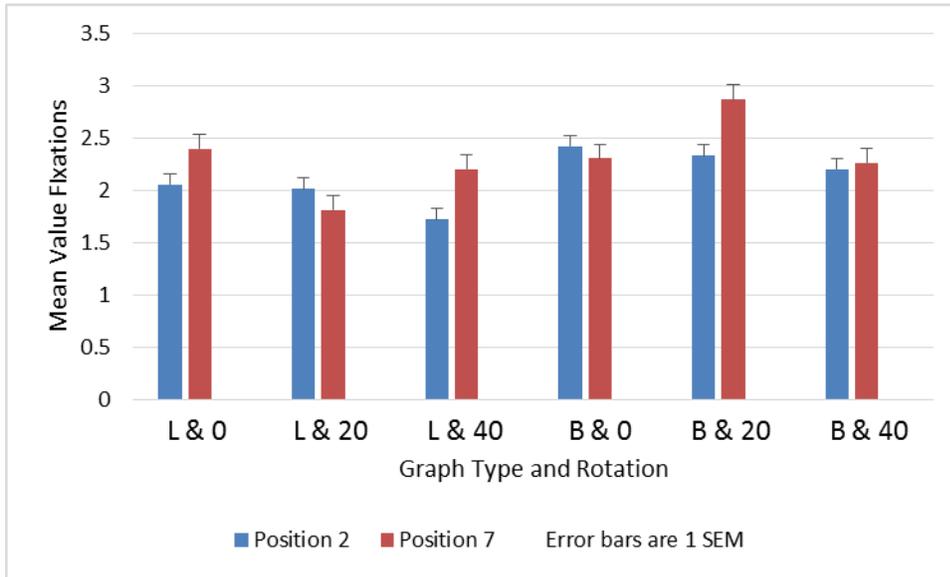


Figure 12. Interaction of rotation, gridlines, and position for value fixation data.

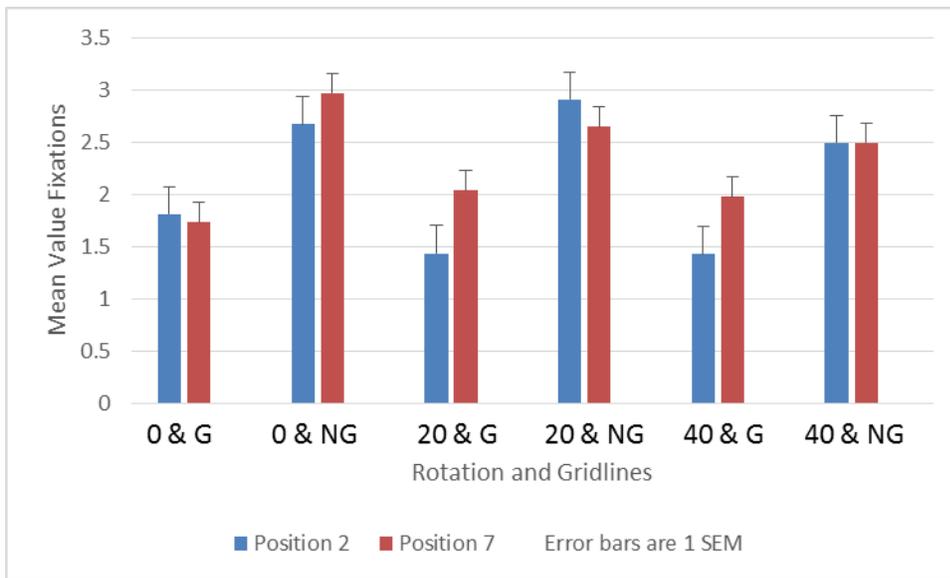


Figure 13. Interaction of graph type, gridlines, and position for value fixation data.

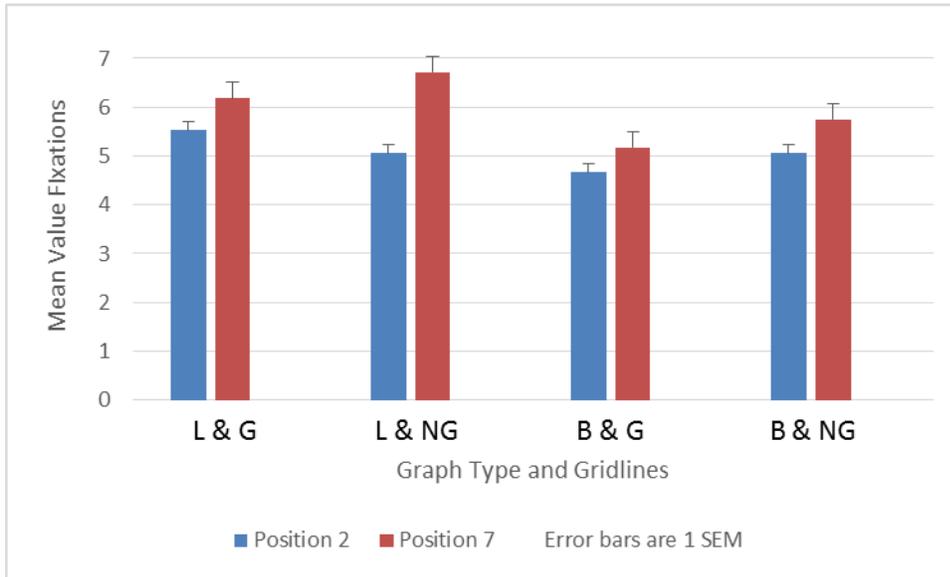


Figure 14. Interaction of rotation, gridlines, and position for value fixation data.

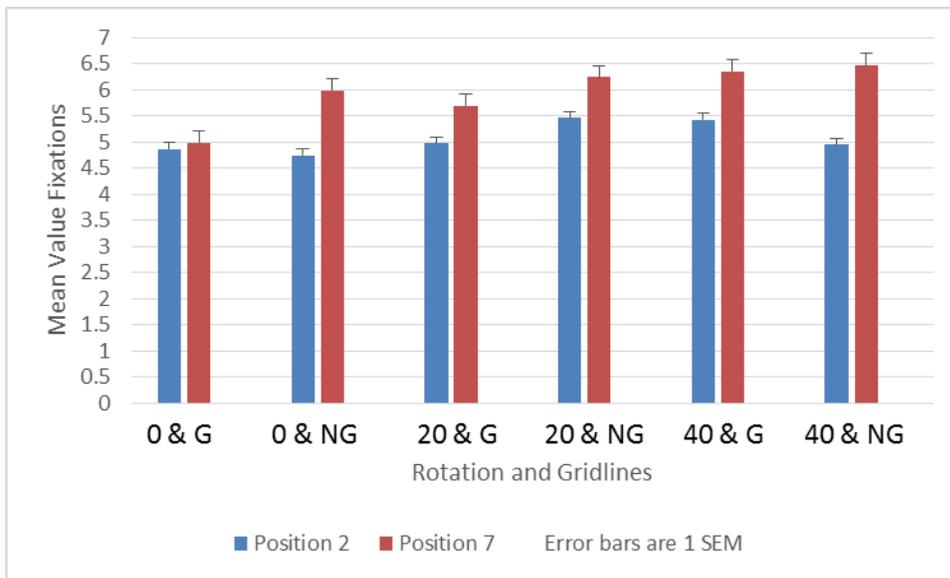


Figure 15. Interaction of graph type, rotation, and position for total time data.

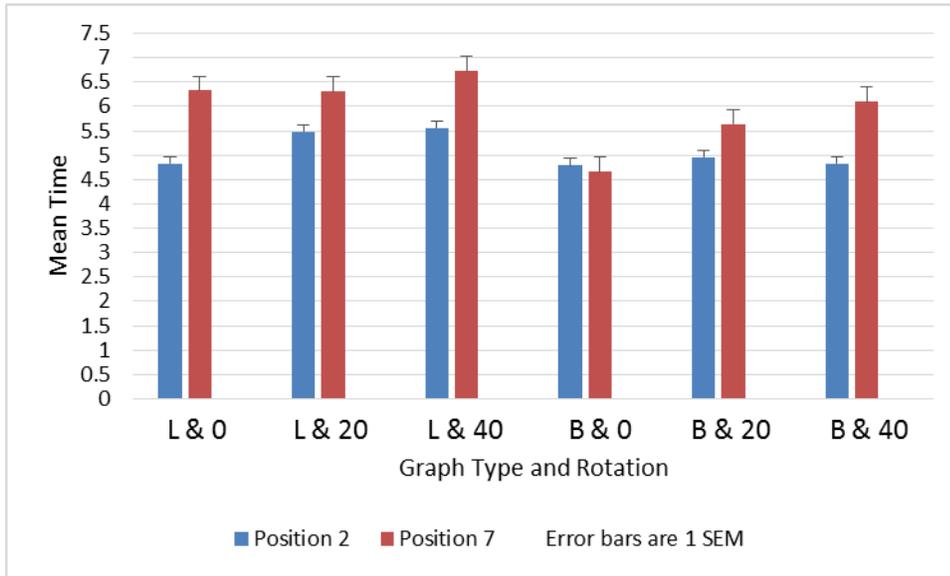


Figure 16. Interaction of graph type, rotation, and gridlines for accuracy data.

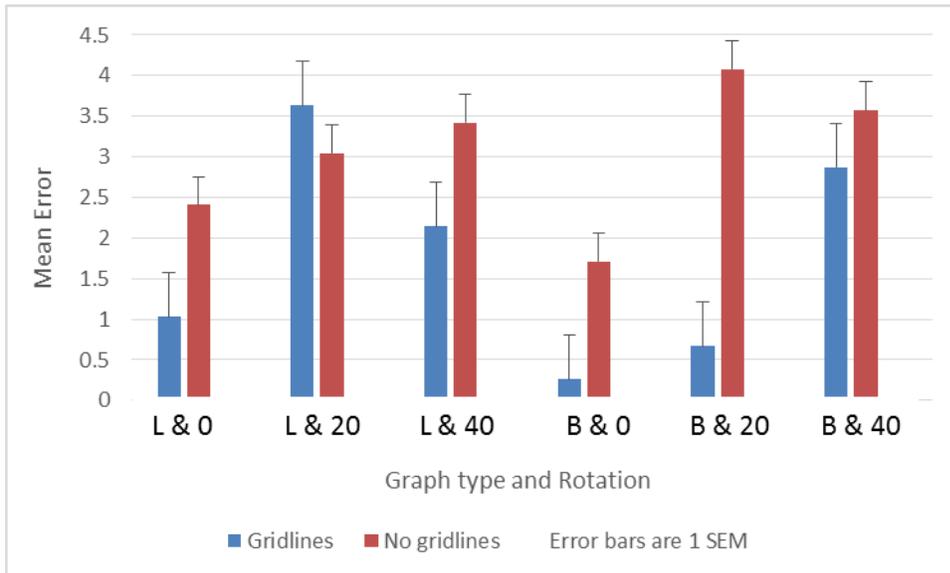


Figure 17. Interaction of graph type, rotation, and position for accuracy data.

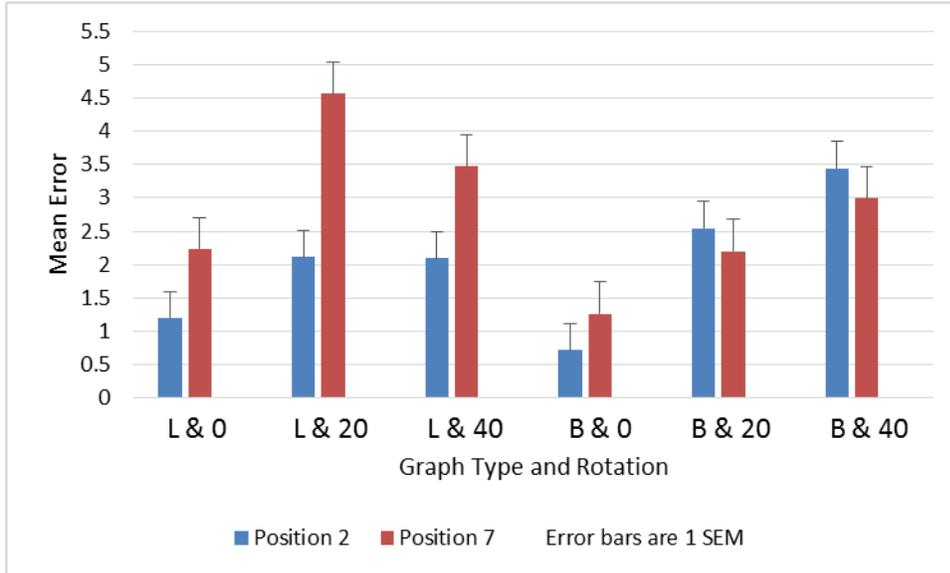
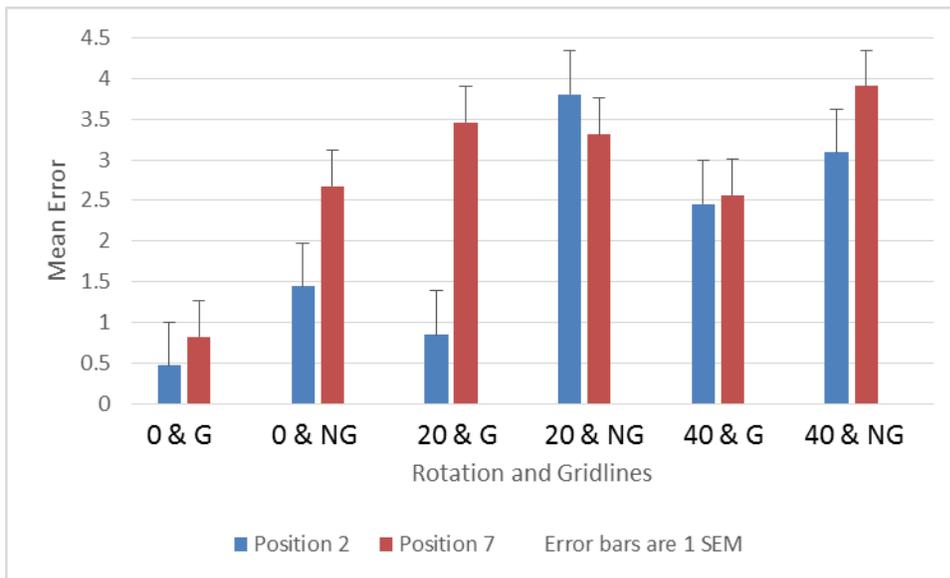


Figure 18. Interaction of rotation, gridlines, and position for accuracy data.



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