GRAPH FORMAT EFFECTS IN PROCESSING HEALTH OUTCOME INFORMATION

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MARK W. POIRIER

B.A., University of Missouri-Kansas City, 2012

Kansas City, Missouri
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GRAPH FORMAT EFFECTS IN PROCESSING HEALTH

OUTCOMES INFORMATION

Mark W. Poirier, Candidate for the Master of Arts Degree

University of Missouri-Kansas City, 2017

ABSTRACT

Decision support tools that incorporate predictive risk estimates can be used to assist patients and their families in making better-informed choices about treatment options. The format utilized to present predictive risk estimates can influence risk perception and treatment decisions. The study reported here investigated the influence of graph format on information processing and decision-making in relation to rt-PA therapy for stroke.

Forty-five older adults were asked to make a hypothetical decision about rt-PA while viewing rt-PA risk information presented in one of three graph formats. Eye tracking, scan path, and transition analysis were used to investigate differences in information processing by graph format.

Graph format did not affect whether or not study participants said yes to rt-PA treatment. There was an effect of graph format on decisional uncertainty, study time, and memory accuracy. Mean fixation densities and common transitions were significantly different by information area, graph format. and time epoch.

Whether graph format alone can influence decision strategies enough to affect choice remains an open question. However, using fixation density and transition probabilities

together appears to be a viable means of inferring information processing and discerning information processing differences.

APPROVAL PAGE

The faculty listed below, appointed by the Dean of the College of Arts and Sciences, have examined a thesis titled “Graph Format Effects in Processing Health Outcome Information,” presented by Mark W. Poirier, candidate for the Master of Arts degree, and certify in their opinion it is worth of acceptance.

Supervisory Committee

Joan M. McDowd, Ph.D., Committee Chair
Department of Psychology

Diane L. Filion, Ph.D.
Department of Psychology

Seung-Lark Lim, Ph.D.
Department of Psychology

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CHAPTER 1

JOURNAL ARTICLE

Graph Format Effects in Processing Health Outcomes Information

Mark W. Poirier

University of Missouri-Kansas City

According to the Centers for Disease Control ("Stroke Facts," 2015), stroke is a leading cause of disability among U.S. adults. Nearly 800,000 people have a stroke each year in the United States, and one in every 20 deaths is due to stroke. Eighty-seven percent of these strokes are ischemic; that is, they involve a blockage or occlusion of a blood vessel ("Stroke Facts"). Recombinant tissue-plasminogen activator (rt-PA) is an Institute of Medicine (IOM) guideline-endorsed treatment for acute ischemic stroke that, if administered early enough, can in effect reverse ischemia-related stroke symptoms and improve patient outcomes (Decker et al., 2015). However, rt-PA may be underutilized due to uncertainty about treatment outcomes combined with fears about the risk of serious bleeding associated with it.

Providing stroke patients and their physicians with a decision tool that includes patient-centered estimates of the risks and benefits associated with rt-PA therapy (including the probability of disability with and without rt-PA) will help alleviate some of this uncertainty and fear and lead to better decision-making and potentially less stroke-related disability. Decker et al. (2015) designed just such a decision tool, and in doing so, they considered several different graph formats as means for articulating outcome probabilities to potential rt-PA recipients. These formats included a vertical bar graph, a stacked bar graph, and an iconic graph. All three graph formats presented outcome information as predictive risk estimates of disability 90 days after treatment with and without rt-PA. Decker et al. ultimately selected a stacked bar graph format for use in their three-page decision-making tool, because information they obtained from focus groups indicated that patients preferred the stacked bar graph and found this format the most informative (Decker et al., 2015).

While inviting meaningful patient collaboration and understanding patient preferences are critical to the development of a decision support instrument, patient preference alone cannot be relied upon as a metric of instrument efficacy. We know from prior research involving patient comprehension and treatment choice that when communicating risk information, graphical format can influence information search, risk perception, and treatment decisions (e.g., Brown et al. 2011; Orquin & Loose, 2013). It is possible that the graph format used to present outcome probabilities may influence patient perceptions of rt-PA treatment for stroke without them knowing it and without affecting their preference for graph format.

Like any decision, deciding whether to receive rt-PA treatment for stroke requires that the decision maker adopt a decision strategy. Payne, Bettman, and Johnson (1993) described decision strategies as sequences of operations for searching through a decision problem space. The graphs that Decker et al. created for their rt-PA decision aid are essentially maps of the rt-PA decision problem space. Each graph contains the same information, but changing the graph format alters the layout of the map. Because the map of the decision problem space is different from one graph format to another, decision processes may also be different.

Making a decision involves weighing available options and the potential outcomes of those options to determine the best choice given a particular set of circumstances (Payne et al., 1993). Each location on the graphs that Decker et al. (2015) created provides different and specific information about options and potential outcomes relevant to the decision about rt-PA treatment. Making a decision about rt-PA treatment requires processing information at these various locations. Eye tracking technology can be used to record a graph reader's eye movements and identify patterns of movement that are indicative of information processing. For example, the order in which visual fixations occur reflects the order that information items are processed; the frequency of fixations to an information item is associated with its relevance or importance; and the duration of visual fixation is related to how deeply the information is processed (Zhou et al., 2016). Together, these variables provide a window into the information processing strategies of the decision-maker.

In the current study we tracked the eye movements of older adults while they processed the information from the Decker et al. (2015) graphs and made a decision about whether they would want a loved one to receive rt-PA. We were interested in differences in visual fixation patterns by graph format that might suggest that format affected which information items were given priority or were most central to the decision.

We know that during the decision process visual attention is generally focused on information deemed most relevant to the decision, while other information is processed less or not at all (Glaholt & Reingold, 2011). The subset of information that is most closely scrutinized during the decision process has been described as a "consideration set" (Howard & Jagdish, 1969), typically containing one to four pieces of information (Shi, Wedel, & Pieters, 2013). In the present study, the required decision was binary, or Yes/No with regard to rt-PA. In a binary decision that involves the assessment of multiple attribute levels and their probabilities, identifying the fixations that occur with greatest frequency immediately preceding the decision may suggest which information was most relevant to the decision-maker; i.e., their consideration set.

While identifying the fixations that occur with greatest frequency immediately preceding the decision may provide information regarding consideration set content, identifying the transitions that occur between those fixations with the greatest frequency may offer insight into active decision processes by identifying important comparisons between information areas being made by the decision-maker. Eye tracking researchers have adapted techniques commonly utilized in computer science and bioinformatics applications to analyze fixation sequence similarity (e.g., West, Haake, Rozanski, & Karn, 2006). If multiple fixation sequences are to be compared, a transition matrix can be constructed that displays the probability that visual attention (fixation) will transition from one defined area of interest to another. We used transition data in the current study to investigate the frequency and order in which older adults fixated important information areas on the Decker et al. graphs and the frequency of transitions between those information areas while making a decision about rt-PA treatment.

The purpose of the graphs designed by Decker et al. (2015) was to facilitate information transfer and decision-making when considering the use of rt-PA following stroke. Our goal with the current study was to investigate whether graph format had an effect on information processing and decision-making in a sample of older adults as they made a hypothetical decision about whether to have a loved one treated with rt-PA for stroke. The present study was designed to address the following questions:

1. Which graph format was most preferred?

2. Did the number of people who said they would want their loved one to receive rt-PA for stroke differ as a function of the graph format that was used to present predictive risk estimates?
3. Were there differences in study time before a decision as a function of graph format?
4. Were there differences in memory accuracy and decisional uncertainty as a function of graph format?
5. Were there differences in study time of separate informational components as a function of graph format?
6. Do consensus fixation sequences differ as a function of graph format?
7. Do participants prioritize certain graph components (create a decision set) in the seconds just before reaching a decision about using rt-PA? If so, does the decision set differ by graph format?

Method

Participants

A convenience sample of sixty-six older adults were recruited through telephone and email solicitation. Twenty-one participants (32%) were excluded from the study due to eye tracking difficulties related to sagging eyelids, pupil obfuscation, and reflective eyewear. Final sample size was n=45. Analysis of variance confirmed that the excluded participants were not significantly different from those retained in regard to age, graphicacy, and numeracy. The average age of participants was 72.3 years (SD = 6.01). Participant demographics are presented in Table 1.1. Older adults were selected as the target population for this study due to the unique impact that stroke has had and is projected to have on this

Table 1.1

Mean Data by Graph Format

	Bar Graph	Stacked Graph	Iconic Graph
Sex	F=12/M=3	F=10/M=5	F=11/M=4
Age	72.80 (5.91)	71.40 (5.94)	72.31 (6.50)
Working With Graphs	9.60 (1.92)	9.53 (1.46)	9.80/13 (2.31)
Working With Numbers	3.93 (1.77)	4.33 (1.78)	3.80/6 (1.57)
Study Time	56.99 (22.93)	39.394 (10.55)	46.712 (17.64)
Memory accuracy	.93 (.80)	1.93 (1.10)	1.67 (.98)
Decisional Uncertainty	9.33(3.02)	6.400 (2.20)	6.87 (2.98)

population. Both prevalence and incidence of ischemic stroke are high in the older adult population. Participants were randomly assigned to one of three study conditions corresponding to the graph format used to present rt-PA risk/benefit information to them. Informed consent was obtained from all study participants, and each participant received $15 as compensation for their participation.

Measures

Demographic Questionnaire – This basic demographic survey includes items such as participant age, level of education, a brief medical history, and a household income estimate.

Working With Numbers (Numeracy) – Numeracy is a key person-level characteristic that can affect health literacy and health decision quality. This measure, which has been used in other health literacy studies, consists of six questions that require a basic understanding of ratios and percentages. Total possible score = six (Brown et al., 2011).

Working With Graphs (Graphicacy) – According to Carpenter and Shah (1998) and many others, "individual differences in graphic knowledge should play as large a role in the comprehension process as does variation in the properties of the graph itself" (p. 97). This 13-question measure assesses an individual's ability to comprehend and use information presented in different graph formats. It was developed for and has been used in prior health literacy and decision aid research. Total possible score = 13 (Galesic & Garcia-Retamero, 2011).

Modified Decisional Conflict Scale (DCS) – Level of decisional conflict is a key outcome measure in this project. This 13-question version of the DCS was used to assess participant level of decisional conflict across three subscales: Decision Uncertainty, Factors Contributing to Uncertainty, and Perceived Efficacy in Decision-making (Katapodi, Munro Pierce, & Williams, 2011).

rt-PA Comprehension/Recall Questionnaire – Study participants were asked nine multiple choice questions regarding the risks and benefits of using rt-PA based on information presented in the graphs and slides.

Equipment

Eyetracker 6000 - An Applied Sciences Laboratories remote eye tracker was used to monitor gaze fixations while the participants were viewing the rt-PA graphs. The eye tracker samples eye position 60 times per second with an accuracy rating of 0.5° visual angle and provides a continuous stream of data including eye position (X-Y coordinates). Participants are seated in a sound-attenuated room that contains a table and chair, computer monitor, and an Applied Science Laboratories D-6 optics module. On a table in front of the participant is a 17-inch computer monitor. The eye-tracking camera is situated in a custom-designed harness just below the computer monitor. The eye-tracking camera receives instruction from and sends data to two computers that are located outside of the booth.

GazeTracker™ software – GazeTracker software by Eyetellect ("Eyetellect: Intellect at the Speed of Sight," n.d.) was used for stimulus presentation, data acquisition, and some preliminary data analysis. In data acquisition mode, GazeTracker converts eye location data provided by the eye tracker into a series of fixations mapped onto to areas of interest (AOIs) corresponding to different graphic elements. Fixations are defined as a minimum of two sampled eye positions occurring with a fixation diameter of 30 pixels with a minimum duration of 100 msec.

Procedure

Participants came to the lab, where basic study procedures were explained to them and informed consent was obtained. Once consent was obtained, they were asked to complete a demographic questionnaire.

The participant was then seated in the eye-tracking booth, the operation of the eye tracker was explained, and a calibration routine was run. Next the participant was shown one of three rt-PA decision aid presentations, depending on which study condition they were randomly assigned to. All three presentations were exactly the same except for the graph format in which example outcome estimates of disability and bleeding were presented. The *Stroke rt-PA Decision Aid Presentation* consisted of text-based and graphic representations of risk/benefit information related to the use of rt-PA (Decker et al., 2015). Study participants viewed the presentation on a 17-inch computer monitor in the form of a

PowerPoint presentation. Three different presentations of 50 slides were developed for this study. All three presentations included the same slides with white text on a black background and differed only in the graph format used to depict the risks and benefits of using rt-PA: (A) bar, (B) stacked, or (C) iconic. All three graphs were presented in gray scale on a black background (see Figures 1.1-1.3).

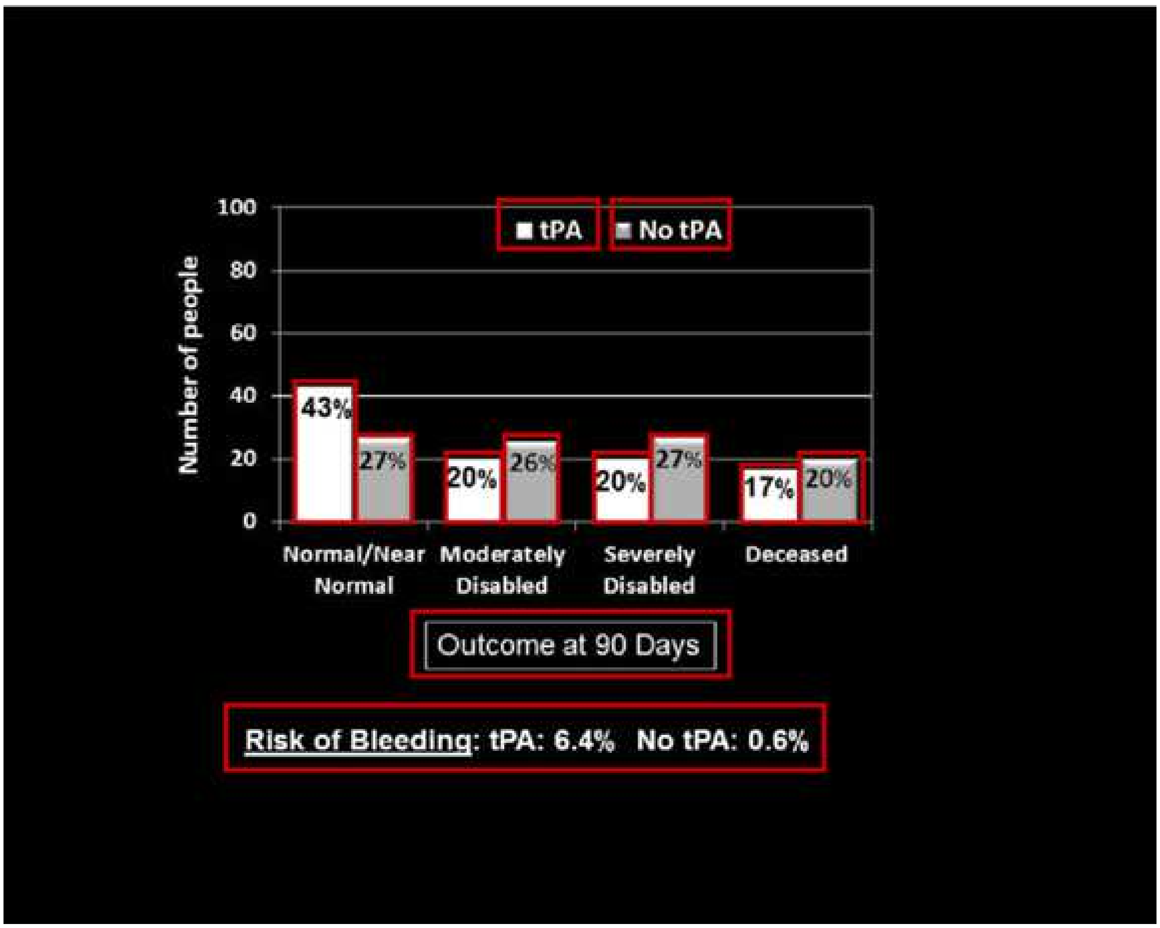

Figure 1.1. Bar Graph with Twelve Visible Areas of Interest

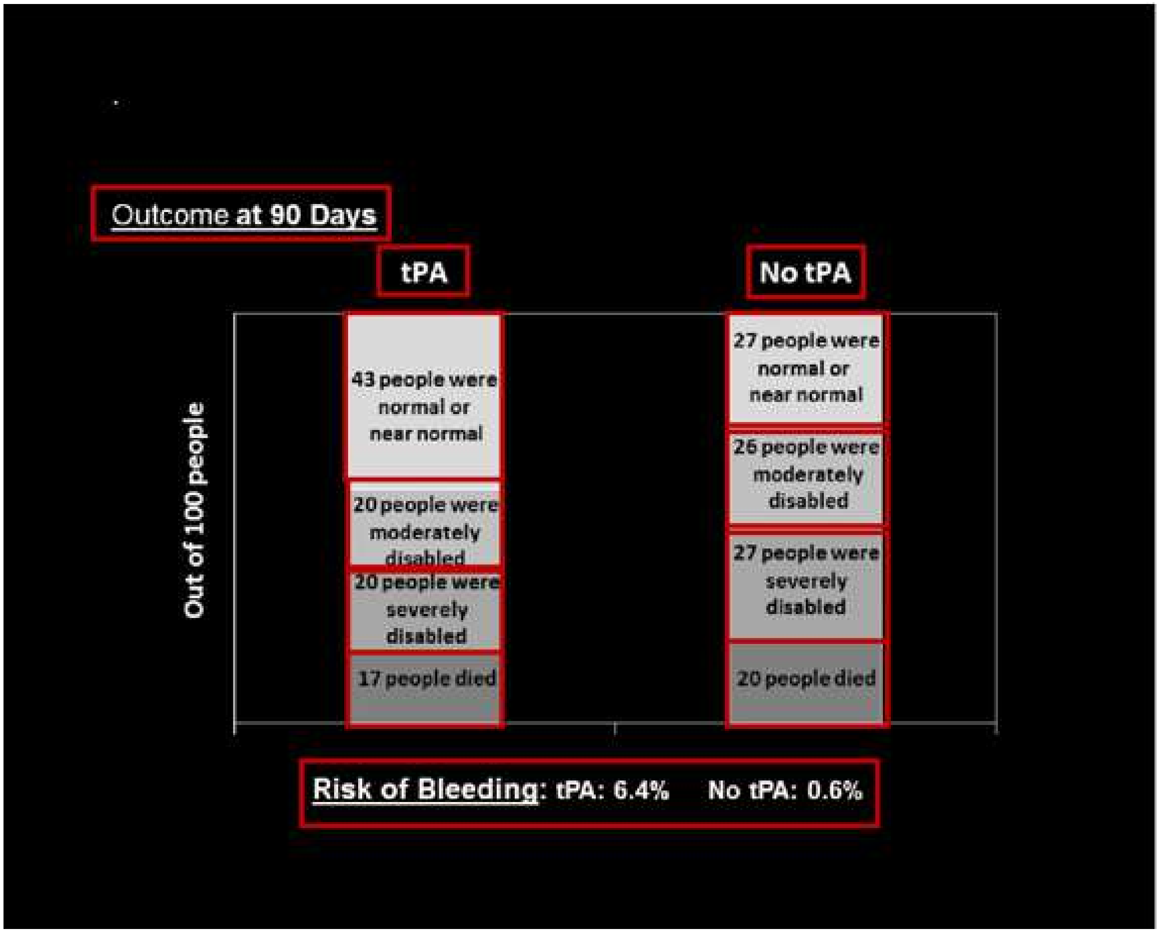

Figure 1.2. Stacked Bar Graph with Twelve Visible Areas of Interest

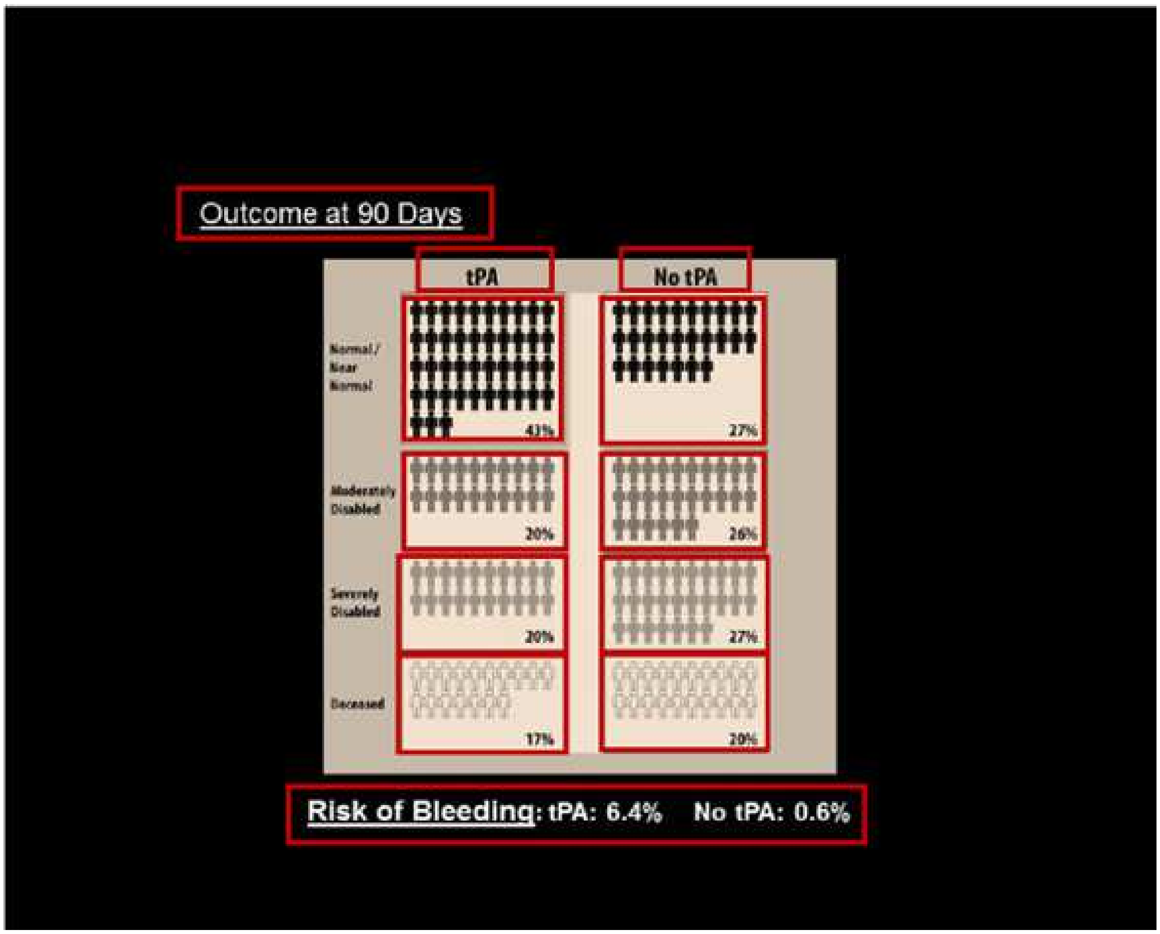

Figure 1.3. Iconic Graph with Twelve Visible Areas of interest

Participants were instructed to read the information presented to them for comprehension and at their normal reading pace, and they were also told that they would be asked some questions about the material later. Following the presentation of some general information about stroke and rt-PA, each participant was asked to (1) imagine a scenario in which a member of their family had suffered a stroke, (2) study a graph which presented estimates of their loved ones' expected level of disability and likelihood of bleeding with and without rt-PA treatment, (3) make a decision about rt-PA treatment, and (4) to tell the researcher when they had made their decision. Once the participant indicated that they had come to a decision, the slide was advanced to a second identical slide and participants were asked to explain that decision. This was done to help define eye movement data collected during the decision phase from eye movement data collected during the decision explanation phase. The presentation duration of each slide was controlled by the participant. Total reading/viewing time for each slide and gaze durations to the presented materials were recorded, including reading time and fixations while the participant considered their decision regarding rt-PA and immediately following that decision as they explained their reasoning for the decision.

After explaining their decision, participants were administered computerized versions of both the Decisional Conflict Scale and the rt-PA Comprehension/Recall Quiz. Directly following the Comprehension/Recall Quiz, they were shown each of the three graph types (bar, stacked and iconic) and asked which graph format they preferred. Participants were allowed to study each graph individually for as long as they wanted and were then shown all three graphs together and asked to indicate which graph format they preferred. Presentation order was controlled when they were allowed to study the graphs individually so that the second graph each participant viewed was always the same graph they had seen in the first part of the study.

At this point, the eye tracking portion of the experiment was complete and the participant was asked to exit the eye tracking booth. Study personnel then administered paper and pencil versions of the Working with Numbers numeracy measure and the Working with Graphs graphicacy measure. Once these two measures were completed, participants were debriefed and given $15 as compensation for their participation.

Results

Because the ability to use and understands graphs and numbers can vary greatly between individuals, we assessed the graphical and numerical abilities of our sample of older adults so as not to confound ability with format effects. Parallel one-way analyses of variance were conducted to compare participant graphicacy and numeric ability scores by graph format. There were no significant differences in graphicacy or numeric ability by format group (both F's < 1.0). Group means for graphicacy and numeric ability are presented in Table 1.1.

Study participants were shown one of the graphs from Decker et al. and asked to make a decision about whether they would want a loved one to receive rt-PA for stroke. Of 45 participants asked, 42 said yes to rt-PA, one said no, and two were undecided. The one participant who said no had studied the iconic graph. One of the participants who was undecided had also studied the iconic graph, and the other had studied the bar graph.

All 45 study participants were asked which of the Decker et al. (2015) graphs they preferred. A chi-square test of goodness-of-fit was performed to determine whether the three graph formats were equally preferred. Preference for the three graphs was not equally distributed, X^2 $(2, N = 45) = 8.933$, $p < .05$. The bar graph was most preferred, followed by the stacked bar graph and then the iconic graph (see Table 1.2).

Table 1.2

Graph Preference

	Frequency	Percent
Bar	24	53.3
Stacked Bar	8	17.8
Iconic	13	28.9
Total	45	100

To examine whether study time differed as a function of graph format viewed, a one-way analyses of variance was conducted. There was a significant main effect of graph format on viewing time [$F(2, 44) = 3.709$, p=.033]. Simple effects test using Tukey's HSD indicated that study times were significantly longer for the bar graph than the stacked bar graph (p= .026). Viewing times were not significantly different between the bar and iconic or the stacked and iconic graphs (p>.05).

The next research questions addressed were whether there were differences in memory accuracy and decisional uncertainty as a function of graph format. A one-way analysis of variance indicated that memory for risk relevant information was statistically different between graph formats [$F(2, 44) = 4.022$, p=.02]. Simple effects tests using Tukey's HSD indicated that those viewing the bar graph remembered less risk relevant information than did those viewing the stacked bar (p=.019). Memory for risk relevant information was not significantly different between the bar and iconic or the stacked and iconic graphs (*p's* >.05).

A parallel 1-way ANOVA also revealed significant differences in decisional uncertainty by graph format [$F(2, 44) = 4.943$, $p=.012$]. Simple effects test using Tukey's HSD indicated that those viewing the bar graph reported higher uncertainty than did those viewing the stacked bar or the iconic graphs (both p's $< .05$), which did not differ from one another ($p>.05$) (see Table 1.1).

To investigate whether the pattern of eye movements observed during graph study differed as a function of graph format, consensus fixation sequences were calculated based on aggregated transition probabilities by graph format (see Figures 1.4-1.6). Visual inspection of consensus sequences revealed that consensus fixation order was similar for the bar and stacked bar graph, while the consensus fixation order for the iconic graph was different from that of both the bar graph and stacked bar graph.

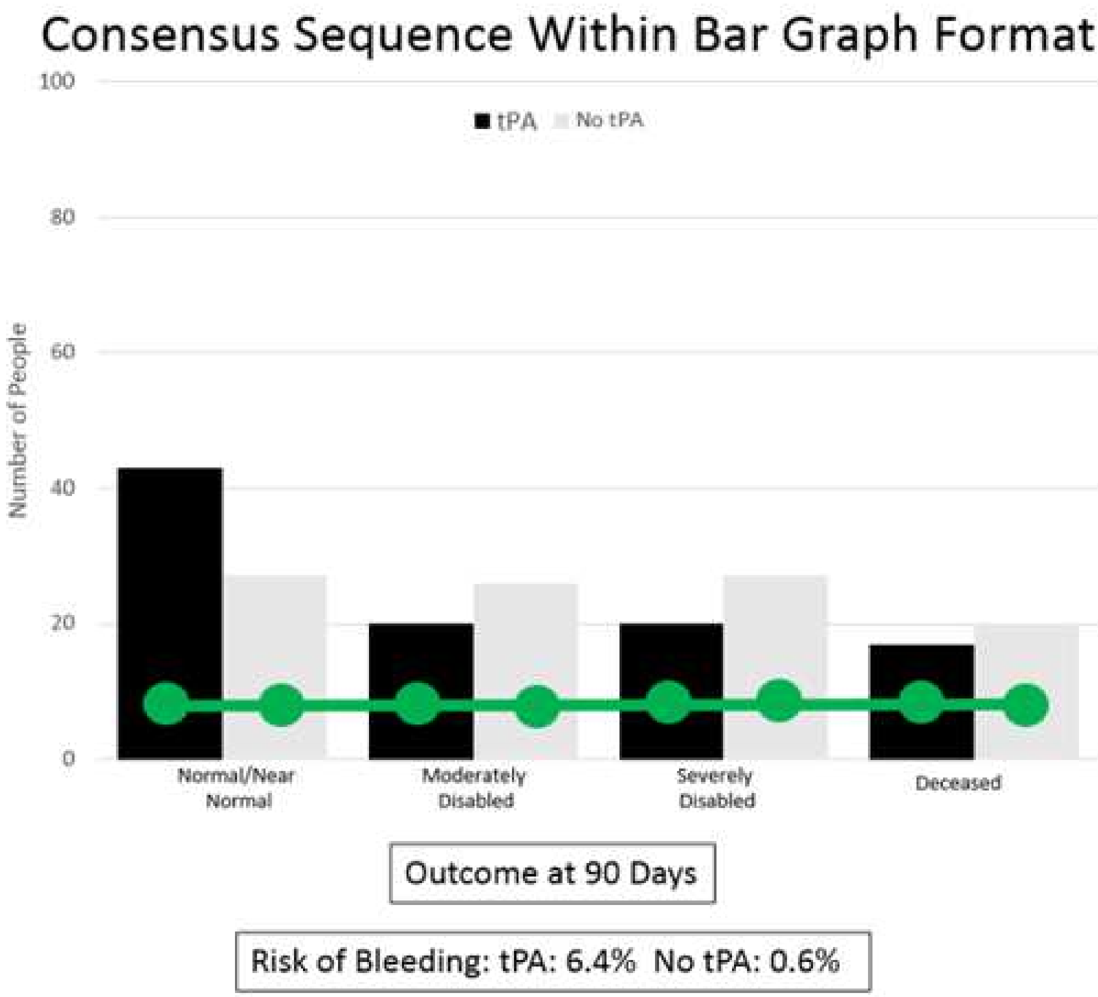

Figure 1.4. Bar Graph with Consensus Fixation Sequence

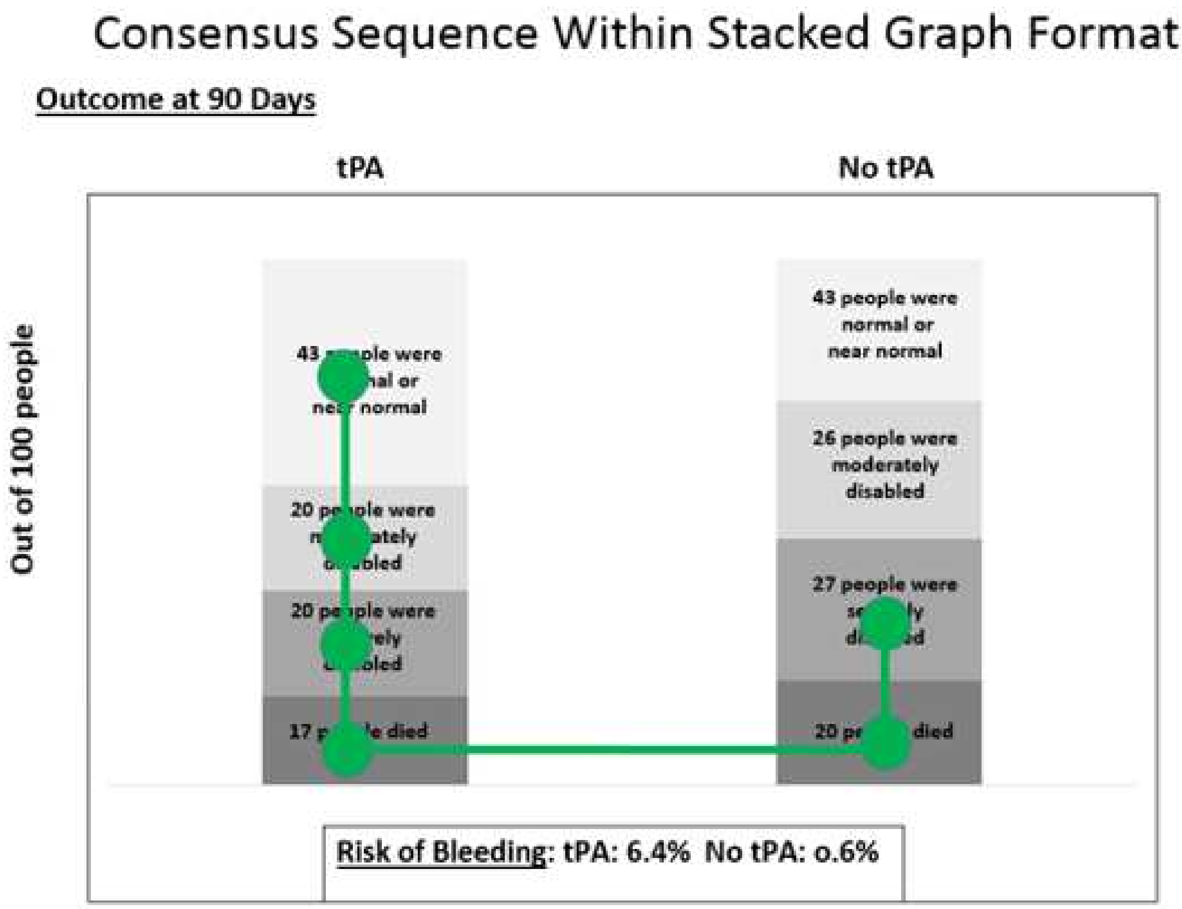

Figure 1.5 Stacked Bar Graph with Consensus Fixation Sequence

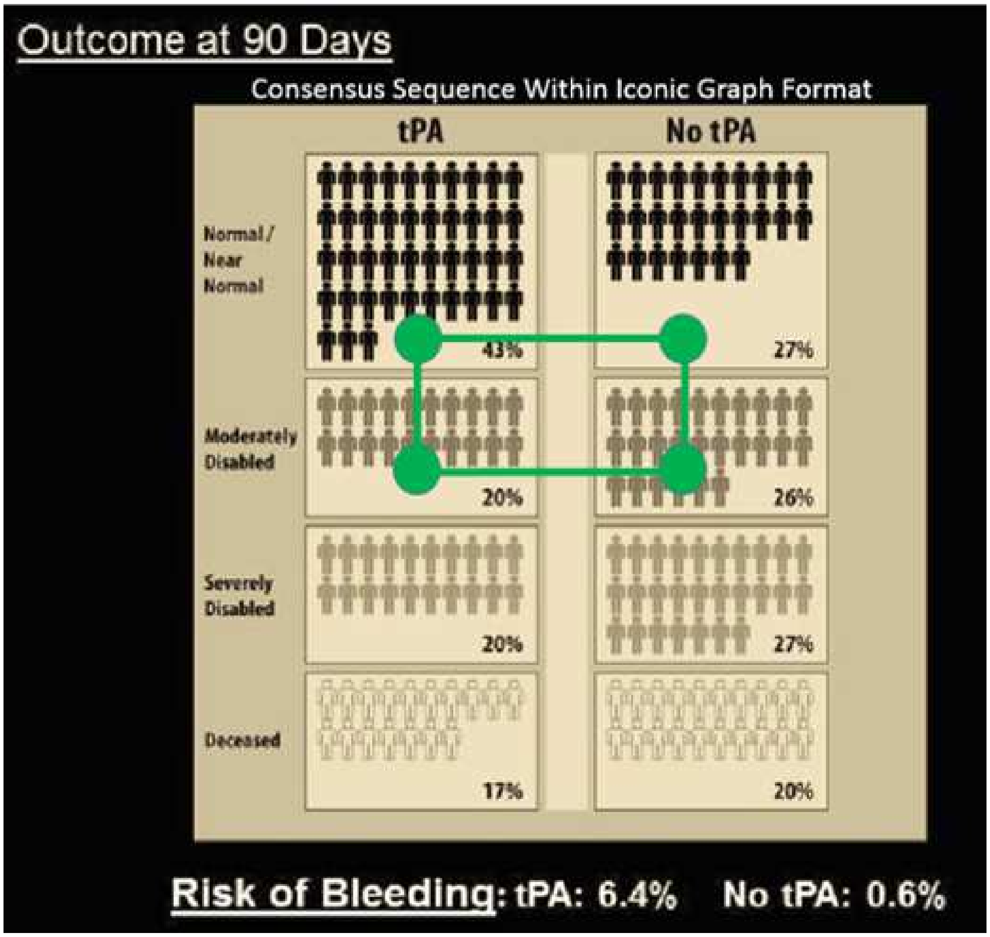

Figure 1.6. Iconic Graph with Consensus Fixation Sequence

Because pre-decision study time varied by study participant, we calculated fixation density as the percent of fixation time in each designated area of interest relative to total fixation duration rather than by simply comparing raw fixation counts and/or durations. Fixation density analyses were conducted to examine whether there were differences in the processing of separate informational components as a function of graph format, whether decision makers developed a consideration set while making their decision about rt-PA, and whether those consideration sets were associated with graph format. Fixation density for 12 defined information areas was calculated for each participant during three different time epochs: the total study time, the last 10 seconds of study time, and the last five seconds of study time. A significant Mauchly's test indicated that sphericity could not be assumed in the data for any of the three time epochs. Greenhouse-Geisser corrected values are reported for all within subjects effects. For total study time, a 3 (graph format) X 12 (information area) analysis of variance was conducted. There was a main effect of graph format [$F(2, 42) = 39.375$, $p<.001$] and information area [$F(4.441, 1186.586) = 23.208$, $p<.001$]. These main effects were qualified by a significant interaction of graph type and information area [$F(2, 186.516) = 7.490$, $p<.001$]. Differences among graph formats were most pronounced for the Normal/Near Normal tPA information area and the Risk of Bleeding information area. Figure 1.7 shows mean fixation density and graph format differences for each information area

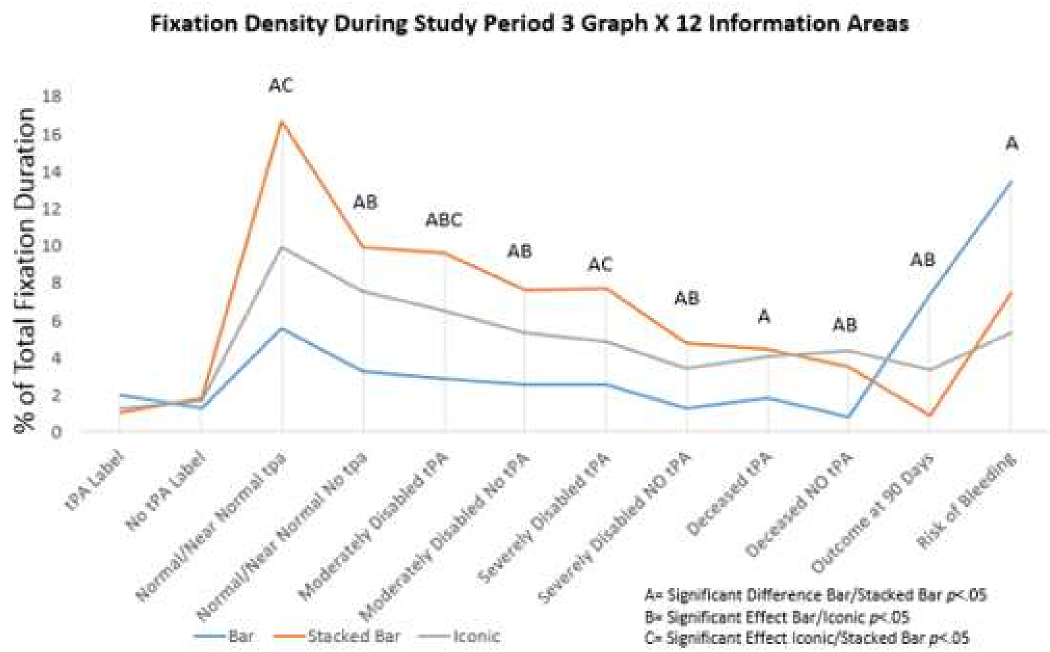

Figure 1.7. Fixation Density during Total Study Time

To investigate whether study participants developed a consideration set while making the decision about rt-PA treatment, a 3 (graph format) X 12 (information area) analysis of variance was conducted to examine mean fixation densities during the last 10 seconds of graph study time. There was a main effect of graph format [$F(2, 42) = 2288.232$, $p<.001$] and information area [F] = 7.214, $p<.001$]. These main effects were qualified by a significant interaction of graph type and information area [$F(9.473, 198.942) = 4.335$, $p<.001$]. Differences among graph formats were most pronounced for the Risk of Bleeding, the Outcome at 90 Days information area, and the Moderately Disabled information area. Figure 1.8 shows mean fixation density and graph type differences for each information area.

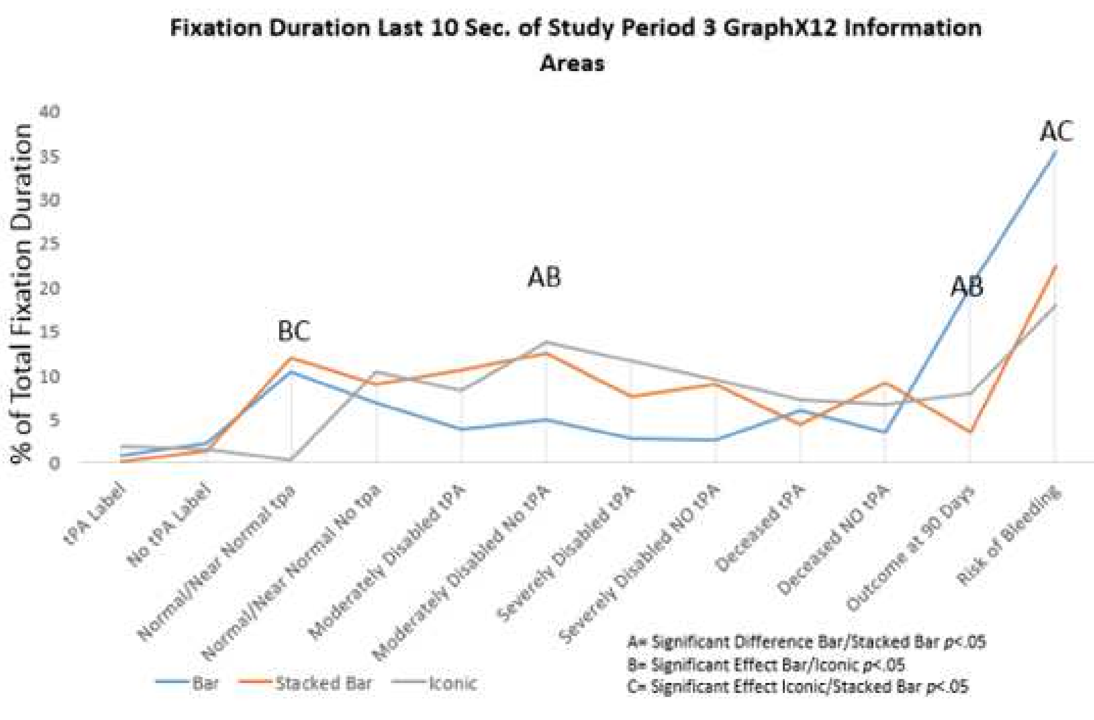

Figure 1.8. Fixation Density during the Last 10 Seconds of Study Time

To further investigate whether study participants developed a consideration set while making the decision about rt-PA treatment, another 3 (graph format) X 12 (information area) analysis of variance was conducted to examine mean fixation densities during the last five seconds of study time. There was a main effect of graph format [$F(2, 42) = 1939.291$, $p<.001$] and information area [F4.737, 198.942] = 7.905, p<.001]. These main effects were qualified by a significant interaction of graph type and information area [$F(9.880, 207.485) = 2.493$, $p=.008$]. Differences among graph formats were most pronounced for the Outcome at 90 Days information area and the Severely Disabled information area. Figure 1.9 shows mean fixation density and graph type differences for each information area.

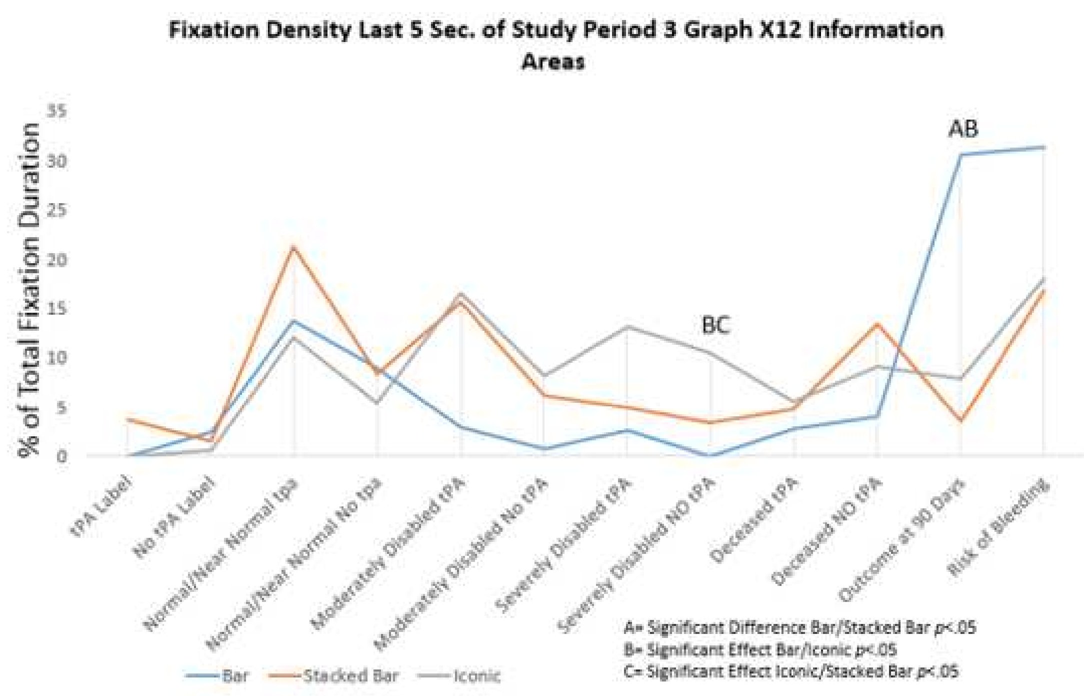

Figure 1.9. Fixation Density during the Last Five Seconds of Study Time

In addition to examining fixation density during three different epochs, the most common transitions between information areas were also tabulated. Transitioning between the Normal/Near Normal tPA information area and the Normal/Near Normal No tPA information area was among the most common across all three graph formats during the total study time. During the last 10 seconds of study time, transitioning between the Normal/Near Normal tPA information area and the Normal/Near Normal No tPA information area was among the most common for the bar and stacked bar graph formats. Transitioning between the Normal/Near Normal tPA and Moderately Disabled No tPA information areas was among the most common for both the stacked bar and iconic graph formats. During the last five seconds of study time, transitioning between the Normal/Near Normal tPA information area and the Normal/Near Normal No tPA information was among the most common for the stacked bar and iconic bar graph formats. There were no other similarities in transition patterns by graph format during the last five seconds of study time. Figures 1.10 - 1.12 show the most common transitions during total study time and during the last five and 10 seconds of study time by graph format.

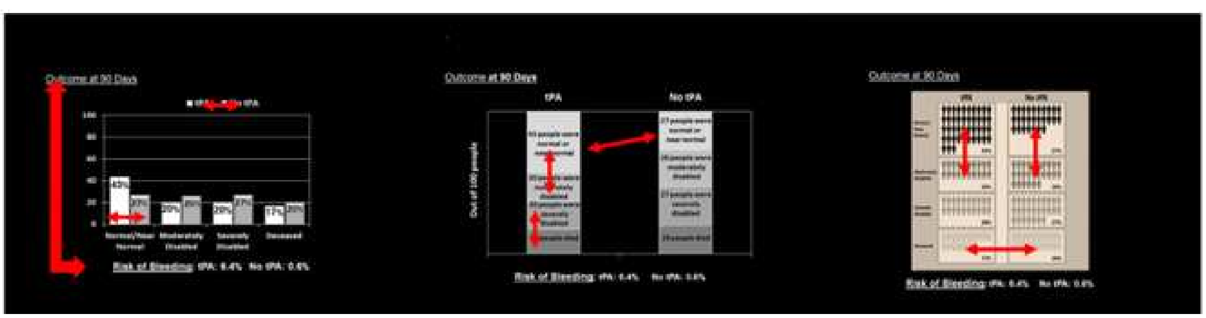

Figure 1.10. Most Common Transitions during Total Study Time

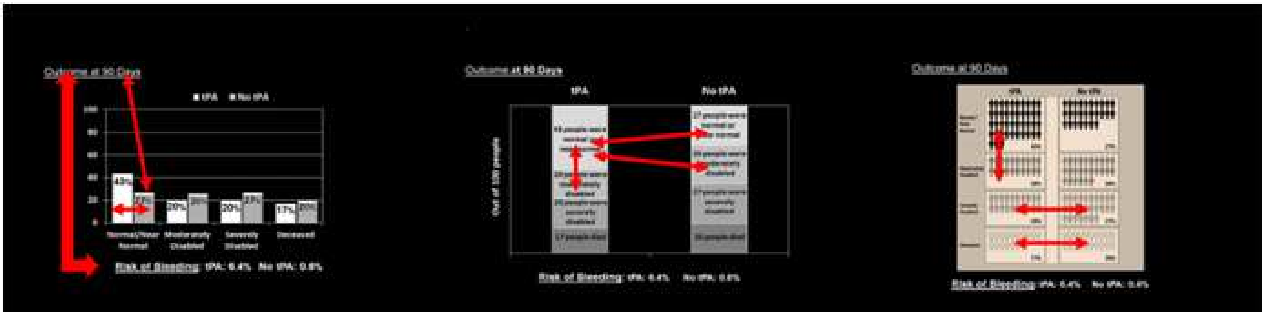

Figure 1.11. Most Common Transitions during the Last Ten Seconds

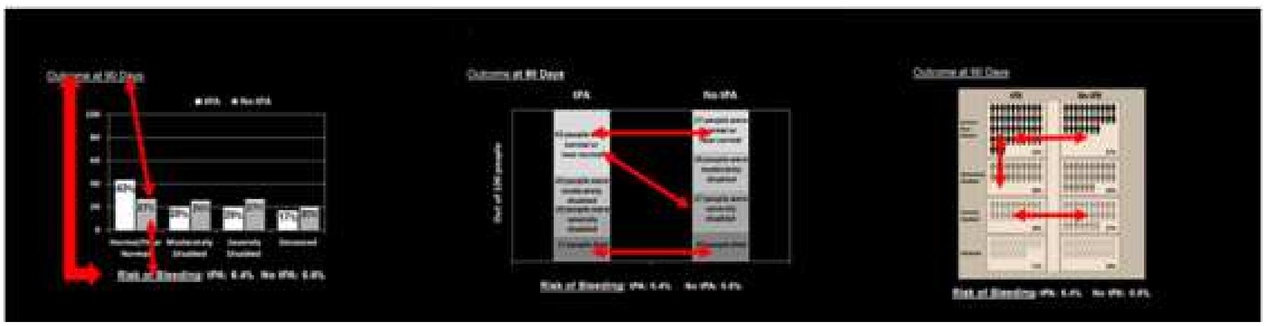

Figure 1.12. Most Common Transitions during the Last Five Seconds

Discussion

The purpose of the current study was to gauge the effects of using different graph formats to present outcome probability information to older adults faced with a hypothetical decision about treating a loved one with rt-PA for stroke. We examined differences in decisional outcomes by graph format such as whether participants ultimately chose to have a loved one treated with rt-PA, and the level of certainty/uncertainty with which they made this choice. In addition to these decisional outcomes, we were also interested in how graph format may have affected information processing and decision-making.

Graph format did not affect whether or not study participants said yes to rt-PA treatment. Only one older adult said they would not want a loved one treated with rt-PA.

This was not a wholly unexpected result. In the current study, all participants were provided the same outcome probability estimates. The risk associated with rt-PA, specifically the risk of bleeding, was low (6.4%), and the potential for improved outcomes (reduced disability) with rt-PA treatment was quite good. There would have had to have been a very large effect of graph format to offset these facts and cause participants to say no to rt-PA. The Decker et al. (2015) decision aid from which the graphs for this study were taken is meant to provide stroke patients with individualized predictive outcome estimates, which would vary depending on the patient. It is possible that graph format might have been associated with choice if the likelihood of improved outcomes were lower or potential risk were higher.

We did find an effect of graph format on decisional uncertainty. Older adults who studied the bar graph were more uncertain about their decision than those who studied either the staked bar or the iconic graph. If the risks associated with rt-PA had been higher and the likelihood of a good outcome less it is possible, that decisional uncertainty about rt-PA treatment may have increased enough to influence decision-making. Overall, the bulk of the evidence collected suggests that the bar graph under-performed in relation to the other two graph formats. Average study time was higher for those who studied the bar graph than for those who studied the stacked bar graph, yet memory accuracy was poorer and as reported, decisional uncertainty was higher. These are interesting findings, especially considering that the majority of study participants said they preferred the bar graph to either of the other two graph formats. It is unclear why the bar graph was preferred by the sample of older adults. It is possible that study participants were more familiar with the bar graph format and chose it by default. It should be noted that these findings are not congruent with those of Decker et al. (2015), who reported that their research showed the stacked graph to be preferred to either the bar or iconic graph formats. Again, there is no clear explanation for this discrepancy in preference, although it may be due to sampling differences. Decker et al. conducted focus groups with stroke survivors and their families whose graph comprehension and numeric abilities were unknown. Participants in the current study were healthy university educated older adults with good graph comprehension and numeric ability. These differences may have contributed to the discrepancy in graph preference.

The data indicate that there were apparent differences in the order and depth with which information was processed as a function of graph format. The consensus fixation sequence generated for the iconic graph is markedly different from those of the bar and stacked bar graphs. However, this does not explain the differences in study time, memory accuracy, and decisional certainty that were observed. Differences in these variables was greatest between the bar and stacked bar graph formats, whose consensus fixation sequences were very similar.

Mean fixation densities were significantly different by information area and graph format. It was expected that mean fixation densities would vary by graph format due to differences in graph construction. Differences in fixation densities suggest differences in information processing. Fixation density was highest in almost every information area for those who studied the stacked bar graph and were lowest in almost every information area for those who studied the bar graph. This pattern of fixation differences may explain the observed differences in memory accuracy. Participants who studied the bar graph spent significantly less time fixated to important information areas than those who studied the stacked bar graph and likely processed the information in those areas to a lesser degree.

Transition frequencies and fixation densities during the last few seconds of study were used to investigate whether study participants constructed a consideration set and whether consideration sets differed by graph format studied.

During the last ten seconds of study time, bar graph viewers transitioned most frequently between the Normal/Near Normal tPA information area and the Risk of Bleeding and Outcome at 90 days information areas. Those who studied the stacked bar graph transitioned most frequently between the Normal/Near Normal tPA, the Normal/Near Normal No tPA, and the Moderately Disabled No tPA information areas. Iconic graph studiers' most frequent transitions were between the Normal/Near Normal tPA, Moderately Disabled tPA, and the Severely Disabled with and without tPA, and Deceased with and without tPA information areas. Overall it seems that graph viewers prioritized comparing the potential of being normal or near normal if treated with tPA and the more dire potential outcomes of disability and death. Only the bar graph views seemed interested in checking the Risk of Bleeding or the Outcome at 90 Days information areas. These findings do suggest that participants may have constructed consideration sets consisting of the most relevant information to the rt-PA decision and that those decision sets varied by graph format studied.

In summary, there seems to be some evidence that graph format played a role in shaping the way that older adults processed outcome probabilities information about rt-PA treatment for stroke. Whether graph format alone can influence decision strategies enough to affect choice remains an open question. Graph format at least in this study was significantly associated with study time prior to decision-making, level of decisional uncertainty, and memory accuracy. Using fixation density and transition probabilities together appears to be a viable means of inferring information processing and discerning information processing differences between groups.

Future Research Implications

Fixation density and transition frequency are promising measures that may prove useful to future researchers investigating the processing of outcome-relevant medical information. Maximizing the number of participants in future studies is recommended. In the current study, fixation density and most common transitions were calculated based on a small number of observations, especially for the 5- and 10-second epochs. An increased sample size would result in an increased number of observations and improved measurement quality. Increasing sample size will also facilitate the investigation of potential format preference effects. In the current study it was not possible to examine whether studying rt-PA information in one's preferred graph format affected decisional outcomes such as uncertainty and memory accuracy because too few participants reported having studied their preferred graph format.

Future studies should also take pains to ensure that information areas identified for measurement are equivalent across experimental groups and that variables such as memory accuracy are measured with the utmost rigor. Memory accuracy in the current study was based on only three questions that required recall of specific risk probabilities. Finally, varying probability estimates of both positive and negative outcomes may elucidate differences in decisional outcomes by graph format. The current study reported that decisional uncertainty was highest for those who studied the bar graph. We hypothesized that if the risks associated with rt-PA had been higher and the likelihood of a good outcome were less, decisional uncertainty about rt-PA treatment may have increased enough to influence some bar graph studiers' decisions. Varying outcome estimates in future studies may help define the extent and magnitude of format effects such as those reported here.

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CHAPTER 2

LITERATURE REVIEW

In 2010, the U.S. Department of Health and Human Services crafted the nation's 10-year health agenda. *Healthy People 2020* outlines key objectives aimed at improving the standard of care health consumers receive by improving both the quality and format of health information offered to consumers as well as improving consumers' ability to obtain and process that information. These objectives included supporting shared decision-making between patients and providers, increasing health literacy skills, and delivering accurate, accessible, and usable health information that is targeted or tailored to the individual. ("Health Communication," 2015).

These objectives reflect a shift away from the traditional provider-centered medical model, in which patients are often treated as passive recipients of care, and toward a more patient-centered service model in which health decision-making is expected to involve the active participation of the patient or consumer. In keeping with the *Healthy People 2020* objectives and incorporating the Institute of Medicine's goals for evidence-based care, which emphasize patient-centered care and respecting patients' individual preferences (Greiner & Knebel, 2003), the Health Outcomes Research Program at St. Luke's Mid-America Heart Institute has developed a database which allows patient-specific data to be used to estimate and model individual patient outcomes during clinical care. Decision aids created from these predictive risk estimates can then be used to assist physicians as well as patients and their families in making better informed choices about treatment options. Studies have shown that these sort of visual aids "are often highly effective, transparent, and ethically desirable tools for improving decision making, changing attitudes, and reducing risky behavior" (Garcia-Retamero & Cokely, 2013, p. 392).

The current study, Improving Health Information about Thrombolytic Therapy for Stroke Part II (iHITTS2), is an extension of an earlier study iHITTS (iHITTS1), which was itself part of a parent study called Rapid Evaluation for Stroke Outcomes using Lytics in Vascular Event, or RESOLVE.

RESOLVE was conducted at St. Luke's Hospital, Kansas City with the intention of developing a decision aid related to thrombolytic therapy following stroke. Through the RESOLVE project, a graphical decision aid was developed to present patient-specific information about the risks and benefits of recombinant tissue-plasminogen activator (rt-PA). RESOLVE employed qualitative methods to identify patient preferences related to variations in graph content and formatting. iHITTS1 was subsequently designed to supplement the patient preference data of RESOLVE with quantitative data regarding the cognitive processing applied in using the decision aid. Specifically of interest was whether information related to the risks and benefits of rt-PA therapy is processed differently when different graph formats are used to convey it.

To provide context for the proposed iHITTS2 we describe the RESOLVE and iHITTS1 studies prior to explaining the study iHITTS2 in detail.

RESOLVE

RESOLVE was developed specifically to address what has been recognized as an underutilization of a clot-busting agent (thrombolytic) called recombinant tissue-plasminogen activator (rt-PA) during the early acute phase of stroke. Stroke is the leading cause of serious, long-term disability in the U.S., and rt-PA has been shown to effectively treat patients with acute ischemic stroke (AIS) and improve patient outcomes (i.e., lessen stroke related disability) if it is administered in the first 4.5 hours of symptom onset. However, there is a low risk of serious bleeding (e.g., intracranial hemorrhage) for some patients associated with rt-PA reperfusion therapy (Miller, Simpson, & Silver, 2011). Decker and colleagues (2015) identified miscomprehension of the risks and benefits (therapeutic uncertainty) involved with rt-PA as an important factor in explaining why it has not been more universally instituted as a routine part of clinical care for patients with acute ischemic stroke. It is estimated that even among ideal candidates for rt-PA therapy (those with the least risk of serious side effects) as many as 40% do not receive the treatment. In fact, only about 7% of all patients with AIS are treated with rt-PA (Decker et al., 2015; Schwamm et al., 2013). A great deal of unnecessary or excess disability might be prevented, even if only the most ideal candidates are treated with rt-PA.

With RESOLVE, Decker et al. (2015) sought to develop a decision tool that would promote informed decision-making and facilitate the decision-making process regarding rt-PA treatment by abating some of the therapeutic uncertainty surrounding its use. Their approach was to design a decision aid that would deliver individualized computer-generated outcome probabilities to potential rt-PA recipients and their families in an emergent care setting to try to maximize risks/benefits comprehension (Decker et al.).

RESOLVE is not the only project to have investigated the use of individualized, computer generated predictive risk estimates in relation to rt-PA therapy. Lee et al. (2015), for example, also recognized the potential value of minimizing therapeutic uncertainty about rt-PA by offering patients individualized outcome probabilities. However, their focus was primarily limited to developing statistical models to calculate those probabilities, and, unlike

Decker et al., they stopped short of addressing the question of how best to communicate them to the patient.

Rather than developing alternative methods of modeling outcome probabilities, Decker and colleagues (2015) utilized a software application suite called Personalized Risk Information Services Manager (PRISM) (Soto, Jones, & Spertus, 2004; Soto & Spertus, 2007) to generate patient risk estimates about rt-PA use. PRISM is an established framework for modeling and presenting predictive risk in clinical situations that has been used to estimate individual outcomes associated with other medical procedures (Chhatriwalla, Decker, Gialde, Jones, & Spertus, 2012a ; Chhatriwalla, Decker, Gialde, Jones, & Spertus, 2012b; Soto, Jones & Spertus 2004; Soto & Spertus, 2007). This web-based tool uses regression modeling to compute predictive models of patient outcomes and can be adapted for use at the point of care. A major benefit of offering patients predictive estimates, which utilize this type of outcomes modeling, is that these models take into account the Heterogeneity of Treatment Effect (HTE). That is, they take into account the fact that individuals vary in their response to a treatment: some derive substantial overall benefit; some derive little benefit; while others are harmed (Patient-Centered Outcomes Research Institute [PCORI], 2013). It is also important to note that HTE analysis predicts the probabilities of both beneficial and adverse outcomes (Varadhan, Stuart, Louis, Segal & Weiss, 2012). An individualized understanding of both the risks and benefits of a course of treatment is an important prerequisite to making an informed medical decision such as whether or not to be treated with rt-PA, where the choice is largely dependent on knowing how well the treatment is likely to work for a particular individual.

Decker and colleagues' RESOLVE project is an example of Patient-Centered Outcomes Research (PCOR). One of the principal goals of Patient-Centered Research is to determine which of the often numerous treatment options available to a patient will work best for them given their circumstances and to convey that information to the patient effectively (Patient-Centered Outcomes Research Institute, 2013). Patient-Centered Outcomes Research strives to help patients answer many questions such as:

1. Given my personal characteristics, conditions, and preferences, what should I expect will happen to me?
2. What are my options, and what are the potential benefits and harms of those options?
3. What can I do to improve the outcomes that are most important to me?
4. How can clinicians and the care delivery systems they work in help me make the best decisions about my health and health care? (PCORI, p. 1)

Guided in part by these patient- centered questions, Decker et al. (2015) employed qualitative research methods to survey stroke patients and their families as well as emergency medicine and neurology clinicians. They were interested in understanding what information would best support decision-making regarding rt-PA treatment and how those data could best be presented. A series of 10 focus groups was convened with a total of 39 stroke survivors and 24 caregivers, as well as structured telephone interviews with 23 physicians and 20 advanced practice nurses to assess "the informational needs and preferred presentation format for those considering rt-PA treatment" (Decker et al., 2015, p. 3). Patient and caregiver focus groups were based on a structured interview, which explored decision-making preferences, level of functional outcome tolerance (disability tolerance), and feedback about multiple potential decision aids for acute ischemic stroke treatment which included graphic representations of rt-PA risk/benefit information. Interviews with the health care professionals were centered on their approach to discussing or consenting to rt-PA therapy with patients and families (Decker et al., 2015).

Ultimately three graph types—a bar graph, a stacked graph and an iconic graph—were considered for inclusion in a prototype rt-PA decision aid as a means of conveying the PRISM generated rt-PA treatment outcome estimates (see Figures 1.1-1.3). All three graph formats presented outcome information as predictive risk estimates of disability 90 days after treatment with rt-PA. A Modified Rankin Scale (Van Swieten, Koudstaal, Visser, Schouten, & Van Gijn, 1988) was utilized to quantify disability levels. The modified scale collapsed the original six levels of severity into four: 1) No significant disability despite symptoms: able to carry out all usual duties and activities, 2) Moderate disability: requiring some help, but able to walk without assistance, 3) Severe disability: bedridden, incontinent, and requiring constant nursing care and attention, 4) Deceased. Likelihood estimates for each level of disability were based on patient specific data and included an individualized estimate of "likelihood of bleeding" with and without rt-PA therapy (see Figures 1.1-1.3).

RESOLVE Summary

The RESOLVE project is an example of patient-centered research undertaken to facilitate decision-making about the use of rt-PA therapy to treat acute ischemic stroke. It was hypothesized that therapeutic uncertainty about rt-PA was hampering the decision-making of both physicians and stroke patients regarding rt-PA use. This therapeutic uncertainty was believed to stem from miscomprehension about the probability of serious bleeding side effects associated with rt-PA. Researchers at St. Luke's Hospital Kansas City used qualitative research techniques to develop a decision aid designed to help abate decisional uncertainty regarding rt-PA therapy. RESOLVE resulted in a three-page prototype decision aid which included graphical presentations of patient-specific estimates of expected disability levels, both with and without rt-PA therapy as well as personalized estimates of the patient's risk of bleeding. Based on their qualitative research findings, the authors of the RESOLVE decision aid decided to adopt a stacked graph format to convey therapeutic outcome estimates to stroke patients and to pattern their instrument after an existing information booklet about thrombolytics (Decker et al., 2015) that was developed at Leads Teaching Hospital (Knapp, Wanklyn, Raynor & Waxman, 2010). The choice to utilize a stacked graph to convey patient outcome estimates was slightly unconventional. Although the Leads pamphlet provided some precedent and their own research suggested the utility of employing a stacked graph format, the majority of existing patient decision support tools use a pictographic (iconic graph) format (Decker et al., 2015).

Improving Health Information about Thrombolytic Therapy for Stroke (iHITTS1)

Decker et al. (2015) had considered several different graph formats as means for articulating outcome probabilities to potential rt-PA recipients. These formats included but were not limited to a vertical bar graph, a stacked bar graph and an iconic graph (see Figures 1.1-1.3). iHITTS1, borrowing from both decision support and usability research, utilized a number of evaluative techniques including eye tracking, to better understand whether graph format might affect older adults' processing, comprehension, and recall of personalized outcome probabilities with and without rt-PA therapy. Of additional interest were whether presenting information about rt-PA via different graph formats would affect a hypothetical decision about whether or not to have a loved one treated with rt-PA, as well as whether the graph format most preferred by older adults would result in the most favorable outcomes; e.g., low decisional conflict and good information comprehension and retention.

Rationale and Relevance of iHITTS1

According to the Centers for Disease Control ("Stroke Facts," 2015) stroke is a leading cause of disability. Nearly 800,000 people have a stroke each year in the United States, and one in every 20 deaths is due to stroke. Eighty-seven percent of these strokes are ischemic; that is, they involve a blockage or occlusion of a blood vessel ("Stroke Facts"). Recombinant tissue-plasminogen activator is an Institute of Medicine (IOM) guideline-endorsed treatment for acute ischemic stroke that, if administered early enough, can in effect reverse ischemia-related stroke symptoms (Decker et al., 2015). However, as mentioned previously, rt-PA may be underutilized due to uncertainty about treatment outcomes and the risk of serious bleeding associated with it. Providing stroke patients and their physicians with a decision tool that includes patient centered estimates of the risks and benefits associated with rt-PA therapy (including the probability of disability with and without rt-PA) will help alleviate some of this uncertainty and lead to better decision-making and potentially less stroke related disability. But, the efficacy of such a decision tool may be highly dependent on how estimates of risk are presented and the degree to which the probabilities of disability are understood and incorporated into the decision-making of stroke patients and their families and physicians.

Population of Interest

Older adults were selected as the target population for this study (iHITTS1) due to the unique impact that stroke has had and is projected to have on this population. Both prevalence and incidence of ischemic stroke are high in the older adult population. In fact, controlling for other risk factors, “the chance of having a stroke approximately doubles for each decade of life after age 55” (“Understanding Stroke Risk,” n.d., para. 13) and according to the most current statistics from the Centers for Disease Control, 66% of persons in the United States who are hospitalized for stroke are over the age of 65. The financial costs of hospitalization due to stroke are estimated at approximately $34 billion annually. The significance of these statistics is sobering when considered in conjunction with census estimates that by 2030, approximately 71.5 million U.S residents will be aged 65 or older (National Network of Libraries of Medicine, n.d.). The already very high costs of stroke both in terms of disability and in terms of financial expense can be expected to rise in coming years, with older adults continuing to be the most profoundly affected population.

Shared Decision-making

Due to the numerous medical options available to health consumers today and the general inclination of the healthcare community toward patient-centered care, taking an active role in one’s health decision-making often means participating in a shared decision process. Shared decision-making (SDM) in a medical context usually refers to decision making that involves a physician or health care professional and their patient. Both parties contribute to the decision-making process and both are assumed to be experts; “the physician is an expert in medicine, the patient is an expert in his or her own life, values and circumstances” (Godolphin, 2009, p. 186). SDM is quickly becoming an important and necessary part of patient-centered care models, but full participation requires that patients understand their health conditions, the treatments that are available to them, and the inherent risks and benefits involved with different treatment options, including no treatment (Kindig, Panzer, & Nielsen-Bohlman, 2004).

Older adults often prefer to take a passive role in health care decision-making (Wolff & Boyd, 2015), be it shared or otherwise. This reluctance on the part of some older adults to engage in medical decision-making means they may be relinquishing agency in these matters to family members or physicians. As a result, the decisions that are made for them may not accurately reflect their values and preferences. One possible reason for this reluctance to participate in decision-making may be that older adults are known to be vulnerable to health literacy deficiencies. Due to these deficiencies, some older adults are actually less able than younger adults to fully participate in making medical decisions such as the decision to receive rt-PA, therapy (Kutner, Greenburg, Jin, & Paulsen, 2006; Serper et al., 2014, Wolff, & Boyd, 2015). It is likely that low health literacy levels in some prospective patients may be contributing to the therapeutic uncertainty surrounding rt-PA and its current underutilization.

Older Adults and Health Literacy

Low health literacy is “a major determinant of morbidity and mortality among older adults” (Kobayashi et al., 2015, p. 1). Thus, it is important to understand this complex construct and its components. The IOM defines health literacy as: “The degree to which individuals have the capacity to obtain, process and understand basic health information and services needed to make appropriate health decisions” (Kindig et al., 2004, p. 2). By this definition, health literacy can be considered to be a “collection of competencies” which encompasses functional ability in reading, writing, and numeracy skills, but also includes cultural and conceptual knowledge and speaking and listening skills (Nutbeam, 2008).

According to the 2003 U.S. National Assessment of Adult Literacy, 29% of older Americans (aged 65 and older) lacked the basic literacy skills required for health management. This means that limited health literacy among older adults may lead to incorrect taking of prescription medication, poor chronic disease management, low use of preventive health services, difficulty making health decisions, and increased risk of mortality (Kobayashi, Wardle, Wolf, & von Wagner, 2014; Reyna et al. 2011). The effectiveness of a medical decision aid like the one developed in the RESOLVE project may depend on whether or not patients are sufficiently health literate to fully understand the information it provides.

Decision Aids/Decision Support Tools

Decision support tools like the one developed by Decker et al. (2015) in the RESOLVE project are specially designed to assist in shared decision-making by educating and informing patients about their treatment options, particularly when there is more than one option available to them, when the advantage of one option over another is not clearly apparent, or when each option has potential benefits and risks that patients may value differently (O'Connor et al., 2009). An effective decision aid considers the user's level of health literacy, presents relevant information in an unbiased way, improves knowledge about treatment options, and promotes realistic expectations about treatment efficacy. In a recent review, Stacey et al. (2014) suggested the following as the primary outcomes of an effective decision aid: (a) Increased knowledge, (b) increased accuracy of risk perception, and (c) increased choice/value congruence (the degree to which patient choices reflect what is important to them).

Stacey also identified other decision-making variables that can be measured: (a) decisional conflict, (b) patient-practitioner communication, (c) participation in decision-making, (d) proportion undecided, and (e) satisfaction.

Stacey et al. (2014) reported that in general there is high-quality evidence that suggests decision aids improve knowledge and reduce decisional conflict. There is at least moderate-quality evidence that decision aids result in improved patient participation in the decision process and improve risk perception via probability estimates. These findings underscore the importance of understanding how specific features of a decision aid can affect decision quality. Two key cognitive components that are directly related to health decision aid comprehension and the understanding of health risks and treatment outcomes information are numeric ability and the ability to read and understand graphs.

Numeric Ability

The ability to understand and use numbers varies from individual to individual, but recent research shows that "low numeracy is pervasive" in the United States (Reyna et al., 2009, p. 2). Often even highly educated adults have difficulty with relatively simple numeracy questions (Apter et al., 2008). According to the 2003 National Assessment of Adult Literacy (NAAL) more than 50% of American adults possess only basic quantitative skills; 22% have no more than the most simple and concrete quantitative skills (Kutner et al., 2006). When making medical decisions that involve numeric information such as risk estimates about treatment options, less numerate individuals may comprehend less, and as a result, they may be more susceptible to framing effects, more reliant upon nonnumeric information such as their own mood states, and less sensitive to varying levels of numerical risk (Reyna & Brust-Renck, 2014). In general, limited numeracy can lead to under- or over-estimation of the risks associated with treatment options, which in turn can translate into poor decision quality and negative health outcomes (Berkman et al., 2011; Reyna et al., 2009). The underutilization of rt-PA therapy is believed to be an instance that typifies the relationship between poor risk comprehension and negative health outcomes (Decker et al., 2015).

We know that in studies that consider patient understanding and treatment choice by comparing risk communication formats, graphical format alone can influence risk perception and treatment decisions (Brown et al., 2011, p. 4). It follows then that to develop the most effective rt-PA decision aid, we need to better understand the role that graph format may play in communicating quantitative risk information about rt-PA to potential patients. As a first step toward addressing this question, we assessed three graphs created for the RESOLVE study. All three graphs presented the same personalized outcome probabilities information related to the use of rt-PA, each in a different graph format. Our goal was to identify the format that produced the best understanding of risk/benefit probabilities in order to promote informed decision-making. A between-subjects design was utilized to compare the effect of graph format [(a) bar graph, (b) stacked graph, or (c) iconic graph (see Figures 1.1-1.3)] on two dependent variables: memory of risk-related information and level of decisional conflict in regard to a hypothetical decision about whether or not to have a family member receive rt-PA therapy. Additionally we were interested in:

a. whether our sample of older adults showed a preference for one graph type over the others
b. whether graph preference differed as a function of educational attainment, numeracy, or graphicacy
c. evaluating whether memory of risk-related information is related to graph preference, time spent viewing the graphs, or visual fixation durations

d. identifying differences in time spent viewing the different graph formats prior to announcing a decision about rt-PA

e. identifying differences by graph type in time spent viewing critical information areas on the graphs

f. evaluating whether differences in time spent considering critical information areas prior to making a decision differ as a function of education, numeracy, or graphicacy may be related to differences in education, numeracy, or graphicacy

g. evaluating whether decisional conflict regarding a hypothetical decision about whether or not to have a family member receive rt-PA therapy is related to visual fixation durations (prior to rt-PA decision announcement)

Graph Comprehension

Although often equated with each other, numeric ability and the ability to understand and read graphs are not the same, nor is graph comprehension merely a sub-type of numeric ability. As defined by Kosslyn (1989), a graph is a form of visual display with at least two scales always being required and values being associated via a "paired with" relation. Graphs represent greater quantities of the measured substance by greater area, longer lines, or more of the symbolized entity (Kosslyn, 1989, p. 186). There are many different types of graphs that can be used depending on what type of data is being presented.

The ability to read and understand graphs can be a critical aspect of medical decision-making. Healthcare providers often use graphic representations to communicate risk/benefit information such as the threat of bleeding and the potential disability outcomes associated with or without rt-PA treatment for stroke. Garcia-Retamero and Cokely (2013) reported that providing visual aids in addition to numerical information about the effectiveness of medical treatments increased accuracy of effectiveness ratings from less than 20% to nearly 80% among people who were moderately graph literate. However, although using graphical representations is generally recommended for facilitating risk comprehension (e.g., Paling, 2003), Galesic and Garcia-Retamero (2011) cautioned that it is not safe to assume everyone intuitively understands graphics or that graph comprehension is equivalent across persons.

Graph comprehension is a complicated, interactive process (Shah, 2002) that is known to be contingent upon a number of factors, including reader ability and the complexity, construction, and format of the graph being read (Kosslyn, 1989). Research has found that indeed, graphs are complex visual representations that contain multiple elements to which a reader must allocate visual attention and which require specific skills and abilities to comprehend (Shah & Hoeffner, 2002). According to Carpenter and Shah (1998), the abilities required for graph reading and comprehension include pattern encoding, retrieving or inferring quantitative relations, and interpreting variable names, scales, and values. A graph reader may also be required to perform computations such as determining the sum of a set of values, finding a mean among values in the data, or the ratio of two values. To perform these tasks, the reader must use information provided at several different locations on the graph including the axis, the title, the legend, and other labels. And, since only a limited amount of information can be held in short term and working memory at one time, some important information areas are given priority; e.g., attention is focused on them for longer periods and or more often. In general, graph readers are believed to process global features and the most salient features of a graph first before engaging in a serial exploration of all or most other features (Friel, Curcio, & Bright 2001; Kim & Lombardino, 2015).

There is good evidence that graph readers perform information search operations that involve the recognition and encoding of graphic patterns, as well as integrative processes that construct or derive meaning from those patterns and relate them to the graph (Ratwani, Trafton & Boehm-Davis, 2008; Shah & Hoeffner, 2002). Carpenter and Shah established that graph readers "form a mental model of the quantitative information displayed in a graph through serial, iterative cycles of identifying and relating graphic patterns to associated variables" (Shah & Hoeffner, p. 173). Eye tracking data confirm that graph readers' visual fixations cycle between different graph regions or visual chunks (e.g., the graphical pattern, axes, legend, title, etc.). As graph complexity (e.g., the number of unique visual chunks) increases, the number of transitions between regions also increase.

Decision-making

Decision-making is a thought process that involves making a choice from available options. The decision maker must weigh options and the potential outcomes of those options to determine the best choice, given a particular set of circumstances. There are many different types of decisions and just as many strategies for making decisions and theories about decision-making. The decision that iHITTS1 participants were asked to make about rt-PA therapy was a hypothetical treatment preference decision. According to Payne, Bettman, and Johnson (1993):

> [A decision strategy] can be thought of as a sequence of operations for searching through the decision problem space. That search may reflect information about such aspects as the relative importance of an attribute-weight or salience, cut off values specifying a minimal acceptable level for attributes and differential preference across attribute levels. Search is often selective and different strategies limit the amount or type of information processed in various ways. (Payne, Bettman, & Johnson, 1993, p. 23)

The weighted additive (WADD) rule is considered a normative or ideal procedure for dealing with preferential decision problems. The WADD rule takes into account the values of each alternative on all the relevant attributes and "the relative importances or weights of the attributes to the decision maker" (Payne et al., 1993, p. 24). "Conflict among values is assumed to be confronted and resolved by explicitly considering the extent to which one is willing to trade off attribute values as reflected by their relative importance or weights" (Payne et al., 1993, p. 24). An overall valuation of an alternative is developed by multiplying the weight times the attribute value for each attribute and summing these weighted attribute values over all attributes. The alternative with the highest overall valuation is chosen. Decision strategies like WADD allow a good value on one attribute to make up for bad values on other attributes, and because of this, they are called compensatory strategies (Payne et al., 1993, pp. 24-27).

While it is true that people sometimes make decisions in ways consistent with procedures like the WADD rule (Payne et al., 1993), they also very often avoid computational strategies that use all available information (Hoffrage,1999), and they may only consider one or two factors at a time (Hoffrage). Generally people appear to make decisions using simple cognitive operations as part of fairly simple decision heuristics (Hoffrage; Payne et al., 1993). For example:

- The lexicographic heuristic (LEX) - the alternative with the best value on the most important attribute is always selected. This process is non-compensatory as a bad value on the most important attribute will ensure that an alternative is never chosen no matter how good it is on another attribute.

- The satisficing (SAT) heuristic - alternatives are compared to a predetermined cut off value, one at a time, in the order they occur. In this case choice may become largely dependent on the order in which alternatives are evaluated.
- The elimination by aspects (EBA) heuristic - the most important attribute is determined and a cut off value for that attribute is determined; all alternatives with values for that attribute that are below the cut off are eliminated. The process is then repeated for the second most important attribute etc. until one alternative remains (Payne et al., 1993).

Decision strategies vary based on situational demands and a host of individual differences; there are no steadfast rules or certainties. Decision makers also commonly use combinations of heuristics; e.g., elimination by aspects (EBA)/weighted additive strategy (WADD). Furthermore, we know that decision makers weight their alternatives differently based on their own values and antecedent experiences and regularly switch strategies partway through the decision process. Older adults are believed to employ decision-making strategies based on age-related cognitive constraints; as a group they tend to use heuristic approaches that are simpler, less cognitively demanding, and require less information integration. "They engage in less thorough information searches and spend more time processing the information they find" (Mata, Schooler, & Rieskamp, 2007, p. 796). Given the nature of the iHITTS1 decision regarding rt-PA therapy, it is likely that iHITTS1 participants, all of whom were adults over 60 years of age, approached the rt-PA decision problem with a value-based strategy considering their probability of disability and the likelihood of serious bleeding both with and without rt-PA treatment. And they very likely employed one or more of the decision heuristics described by Payne et al. (1993).

Eye Movements in Decision-making

A recent review of eye movements in decision-making (Orquin & Loose, 2013) examined theoretical predictions concerning the role of attention in decision-making. The authors either confirmed or reject predictions based on a preponderance of empirical data. Their findings underscore the limitations of heuristic and theory driven schemas of the decision-making process and support the notion that presentation format affects both information search and decision-making.

Orquin and Loose (2013) confirmed that although heuristics are known to be employed in visually-based decisions, the particular heuristic employed by a decision maker is not the sole determinant of attentional focus. Eye movements are partially driven by task demands and partially by stimulus properties. Further, while Orquin and Loose were able to confirm that decision heuristics do result in specific patterns of attention distribution (fixations), they acknowledged that attempts to identify a given heuristic based on attention distribution have been largely unsuccessful. They concluded that a "final decision emerges, not as a simple application of preferences and heuristics to choice stimuli but, through complex interactions among stimuli, attention processes, working memory, and preferences (Orquin & Loose, 2013, p. 203) (see Figure 2.1).

iHITTS Background Summary

rt-PA therapy for stroke is underutilized, probably because the risks and benefits of the treatment are misunderstood by both physicians and patients alike. The underutilization of rt-PA has resulted in unnecessary disability in stroke survivors. A prototype decision tool has been designed to assist stroke patients in deciding whether or not to receive rt-PA therapy. The decision aid includes individualized estimates of the probability of specific

(1.1) Information acquisition is complete and no information is ignored. All information is fixated.	Rejected. Findings on nonattendance falsify this tenet
(1.2) Information acquisition is incomplete and attributes are discounted in the structural model based on the level of attendance.	Confirmed. Nonattendance has down-stream effects on decision making
(2.1) The particular heuristic employed by the decision maker determines visual attention.	Rejected. Visual attention is driven both by bottom up and top down processes.
(2.2) Each heuristic results in a particular distribution of attention.	Confirmed. Experiments manipulating heuristics confirm this.
(2.3) The underlying heuristic can be inferred from the distribution of attention.	Not confirmed. Attempts to classify heuristics based on attention are largely unsuccessful
(3.1) The fixation process is stochastic, and fixations are assigned to the alternatives in an alternating pattern	Rejected. Task demands flexibly control allocation of fixations, alternating or not.
(3.2) Fixation patterns should not change over the course of the decision process because the fixation process is stochastic	Rejected. Findings on attention phases falsify this.
(3.3) The last fixation should be shorter than the mean fixation duration because the fixation is interrupted when the threshold is reached.	Confirmed. The theoretical interpretation, however, assumes evidence accumulation.
(3.4) Fixation durations follow a fixed distribution given by the difference between the best and the worst alternative in the choice set.	Rejected. Fixation durations vary according to many factors such as attention phases presentation effects and time pressure
(3.5) The last fixation is to the chosen alternative.	Confirmed. Higher likelihood of fixating the chosen alternative during entire decision task.
(3.6) A choice bias exists in favor of the alternatives fixated first and last because these alternatives have accumulated more evidence.	Confirmed. The theoretical interpretation assumes evidence accumulation.
(3.7) The accumulated evidence determines choices.	Not confirmed. See section on down-stream effects.
(3.8) Any process that exogenously interferes with the accumulation of evidence toward an alternative will bias the decision in favor of that alternative	Confirmed. Bottom up attention capture can, for instance, affect choices.
(3.9) The information sampling needed to reach a decision increases as options become more similar.	Confirmed
(4.1) Information acquisition consists mainly of screening of information which is reflected in an even distribution of single fixation durations.	Rejected. Fixation durations change during the decision process. See section on utility effect
(4.2) The feature currently highlighted in the decision process, such as the favored alternative or most important attribute, receives attention.	Confirmed
(4.3) The information sampling needed to reach a decision increases as alternatives become more similar which reflects the difficulty of maximizing coherence.	Confirmed
(4.4) Salient alternatives will initially attract more attention and are, ceteris paribus, more likely of being chosen.	Confirmed

Figure 2.1. Predictions concerning Eye Movements and Decision-making (Orquin & Loose, 2013)

levels of disability with and without rt-PA treatment as well as a precise estimate of an individual's risk of bleeding. Providing this sort of patient-specific information should help to reduce patient uncertainty about treatment outcomes of rt-PA and facilitate an informed, shared decision-making process involving both patient and physician. This shared decision process is expected to lead to better decision quality and lower excess disability levels.

Eye Movements and Processing Stages in Decision-Making

Payne et al. (1993) suggested that decision strategies involve sequences of operations for searching through a decision problem space. If we assume this implies an actual visual search of decision relevant information, then it makes sense to track attentional focus via eye movements as a means of tracing decision processes. Regardless of the particular strategy or heuristic employed, decision makers seem to "parse their decisions into sequential (visual) attention tasks such as obtaining an overview, finding relevant alternatives, comparing relevant alternatives, checking chosen alternatives, and so forth" (Glaholt & Reingold, 2011, cited in Orquin & Loose, 2013, p. 197). It has been reported that graph readers process information in a similar fashion; processing global features and the most salient features of a graph first before engaging in a serial search of features and retrieving or inferring quantitative relations (Carpenter & Shah, 1998, Friel, Curcio & Bright, 2001; Kim & Lombardino, 2015).

Through the use of eye tracking technology, it is possible to recognize eye movements (specifically fixation patterns) which are indicative of the sort of attention tasks described by Glaholt and Reingold (2011), Carpenter and Shah (1998) and many others. Sequential attention tasks have been presented in the literature as specifying different stages of processing, each task mapping onto a different stage in a decision-making model (Gidlöf, Wallin, Dewhurst, & Holmqvist, 2013; Glaholt & Reingold, 2011; Orquin & Loose, 2013; Russo & Leclerc, 1994). For example, when faced with a multi-alternative decision, a decision maker will often employ some form of an early screening/orientation stage and a later evaluation/comparison stage (Friel et al., 2001; Gidlöf et al., 2013; Glaholt & Reingold, 2011; Kim & Lombardino, 2015; Orquin & Loose, 2013; Payne et al., 1993; Russo & Leclerc, 1994). The rt-PA decision from the iHITTS1 study involved a binary decision (yes or no to rt-PA) rather than a multi-alternative decision. However, the decision maker was offered several outcome probabilities he or she might choose to consider as they formulated their decision. It is anticipated that processing stages for this sort of decision which involves the assessment of multiple attribute levels (disability levels in this case) and their probabilities in a binary choice may in fact be quite similar to those involved in multi-alternative decision-making.

A process model of the iHITTS1 decision about rt-PA treatment, based on earlier decision models proposed by Russo and Leclerc (1994) and Glaholt and Reingold (2011), might be expected to include four stages:

- Orienting
- Screening of salient or decision-relevant information
- Evaluation and comparison of the most decision-relevant information
- Decision

Each of these stages is briefly described below.

Orienting

In the context of decision-making, orienting involves becoming acquainted with the decision space. In this case, the decision space is a graph presenting outcome probabilities for stroke patients who receive rt-PA therapy. Evidence suggests that graph readers process global features and the most salient features of a graph first (Friel et al., 2001; Kim & Lombardino, 2015). Graph readers might be expected to gather initial information at the graphs axis, the title, the legend, and other labels as they familiarize themselves with the graph's layout, comprehend the type of information presented at the different areas of the graph, and take note of obvious visuospatial differences that might denote quantitative differences. Orienting as described here is in effect an "organizing overview."[1]. But even at this early stage, information with greater decision relevance (from the decision maker's point of view) may receive more attention than other information (e.g. more fixations or longer fixations).

Screening

Screening as conceived of here involves the decision maker's understanding how information areas are related to one's self and determining what information is most relevant to the decision process. A key characteristic of such a screening process is that stimuli are encoded to a different degree depending on their relevance to the decision task. As Glaholt and Reingold (2011) suggested, encoding is not expected to be "uniform across decision alternatives, meaning highly relevant alternatives are processed more deeply, and poor alternatives are processed to a lesser extent, or possibly even excluded from further processing" (Glaholt & Reingold, p. 141). In fact, decision makers may

[1]Excluded alternatives are sometimes reintegrated into the consideration set later in the decision process (Orquin & Loose, 2011).

exclude all but a subset of the most relevant information to the decision at hand[2] (Glaholt & Reingold (2011). Howard and Jagdish (1969) described the subset of alternatives that are under closest consideration during decision-making as a consideration set. Shi, Wedel, and Pieters (2013) found that the number of alternatives in a consideration set varies between one and four alternatives.

The screening stage in a multi-attribute decision (like the one regarding rt-PA treatment) may include serial, iterative cycles of fixation and re-fixation as the decision maker selects the most relevant information and eliminates less important information from their consideration. Eye movements during the screening stage may also reflect a heuristic or heuristics adopted by the decision maker.

Evaluation and Comparison

There is likely considerable overlap between screening and evaluation/comparison stages. It is almost certain that some level of dual processing occurs during the decision process. That is to say, some evaluation occurs during the screening stage (Russo & Leclerc, 1994) which may make it difficult to distinguish screening from evaluation/comparison. Further, both stages involve serial, iterative cycles of attention allocation that may appear quite similar. However, evaluation and comparison should occur later in the decision process than screening. Additionally, although the evaluation and comparison stage may include more than the four-alternative consideration set suggested by Shi et al. (2013), this stage should contain more paired comparisons of consideration set information, and fixations should be longer and more frequent than during the screening stage.

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[2] Excluded alternatives are sometimes reintegrated into the consideration set later in the decision process (Orquin & Loose, 2011).

Decision

The last few fixations in multi-alternative and preference decisions tend to be concentrated on the chosen item (Glaholt & Reingold, 2011). It is probable that in a binary decision that involves the assessment of multiple attribute levels (disability levels in this case) and their probabilities, the last few fixations prior to announcing a decision will be focused on the most relevant information, outcomes, or attributes (from the decision-maker's perspective).

Summary of Key Assumptions about Eye Tracking the Visual Decision Process

Visual fixations are an accepted measure of attention; as such, the position of visual fixations generally indicates what information is being processed. The order in which visual fixations occur reflects the order in which information items are processed. The frequency of fixations to an information item is associated with the relevance or importance of the information, while the duration of visual fixation is related to how deeply the information is processed (Zhou et al., 2016). Fixations during the orienting stage are generally shorter than fixations later in the decision process, but differential encoding according to decision relevance is expected. An attentional bias may exist such that the most relevant decision information may be fixated longer than other information, even at this early stage of the decision process. There may also be a bias such that the most relevant information is fixated more often, especially during the evaluation/comparison stages and just prior to a decision announcement (Glaholt & Reingold, 2011; Russo & Leclerc, 1994).

Although it is assumed that decision makers employ heuristics when making decisions, it may not be possible to discern the specific heuristics that were utilized to make a decision from a decision maker's pattern of visual fixation. The dynamic and changeable nature of the decision process may lead decision makers to switch strategies in the middle of a decision or to make multiple fixations that do not comply with heuristic parameters but which are necessary. For example, when processing complex decision stimuli, multiple fixations may be used as a means of updating working memory. It should also be noted that a certain level of randomness exists in each decision maker's fixation patterns such that a portion of their eye movements cannot be meaningfully qualified. Overall, it may be easier to use fixation patterns to distinguish decision stages such as those outlined in the proposed stage model of visual decision-making rather than to identify the use of specific heuristics.

Comparing Visual Fixation Patterns

String Edit and Sequence Alignment Techniques

Although most commonly utilized in computer science and bioinformatics applications, string editing and sequence alignment techniques have also been adapted by eye tracking researchers (e.g., West et al., 2006) to compare patterns of visual fixation (scan path similarity). Adapting these procedures for scan path similarity analysis requires first transforming recorded visual fixation sequences into strings of characters, with each character in a string corresponding to an area of interest on a visual stimulus. Sequences or strings of characters can then be constructed that represent the temporal order, location, and frequency of the visual fixations that make up a particular scan path (see Appendix A).

Levenshtein Distance

Levenshtein distance is a measure of difference between two sequences or "strings" of alpha numeric characters. A "distance" is arrived at by calculating the number of editing operations required to transform one string of characters into the other. Three types of editing operations are permitted: insertions, deletions, and substitutions. Insertions and deletions are assigned one penalty point each, and a substitution counts for two points. The greater the string edit distance (point value), the less similar the scanpaths are.

The Levenshtein distance between character strings is a measure of difference or dissimilarity between scan paths. However, with the introduction of two additional steps to the calculation procedure, the Levenshtein distance can be converted from a difference measure to a measure of similarity. The number of editing steps required to transform one string into the other must be calculated and the penalty value for those steps summed. The total penalty value is then divided by the number of characters in a string (the longer string if they are not of equal length) and subtracted from one. This method yields a similarity value between 0 and 1, where 1 indicates identical strings (Foulsham & Underwood, 2008) (see Figure A1).

The Needleman-Wunsch Algorithm (NWA)

The Needleman-Wunsch algorithm (NWA) is a global alignment algorithm that attempts to align character sequences in a manner that highlights their similarity. In its simplest form, the NWA allots +1 point for each matching character, -1 point for a mismatch, and 0 points for a gap (see Figures A2 and A3). This alignment method allows for the construction of longer unbroken alignments, which can consist of subsequences of characters separated by a number of mismatched characters. The mismatched characters constitute a gap. Imposing a zero point gap penalty makes it possible to compare sequences that may not begin at the same location or are of unequal length without excessive penalty for mismatches.

String edit and sequence alignment techniques are effective methods of analysis when the goal is to quantify similarity/dissimilarity between two scan paths. However, these methods do not allow for the comparison of multiple sequences at the same time. To compare multiple fixation sequences, it can be helpful to construct a distance score matrix and/or a transition matrix. A distance score matrix displays similarity scores between a number of fixation sequences so their similarity can be assessed at a glance (see Figure A4).

Transition Matrix

A transition matrix is a table that displays the probability that visual attention (fixation) will transition from one area of interest to another (see Figure A5).

Understanding where the eyes look immediately before and after viewing each area of interest helps identify common scanning sequences across participants both within and between graph formats. Ellis and Stark (1986) established that the frequency that visual fixations shiftt or transition to a given area of interest is statistically dependent upon the previously visited area of interest (cited in West et al., 2006). They performed a chi-square goodness-of-fit test of transition frequencies from their research participants' fixation sequences and those that resulted from a stratified random sample. They determined that "Chi-square analysis can be expanded to determine whether a statistically significant difference between the transitions in two sequences or groups of sequences exists" (West et al., 2006, p. 150).

In light of this evidence, even though there has been much speculation about how best to construct an average or consensus scan path from a group of scan paths (and indeed whether such a scan path is even meaningful), it may be possible to construct average scan paths for each graph format using fixation data and aggregated mean transition probabilities (Hembrooke, Feusner & Gay, 2006; Holmqvist et al., 2011). Comparing these average scan paths from each graph format with each other and with individual scan paths may elucidate information processing differences that are a function of graph format.

Summary of Analysis/Techniques for Finding and Defining Scan Path Similarity

- String edit and alignment techniques provide a means of quantifying the similarity/dissimilarity of two scan paths.
- A distance score matrix displays the similarity scores of a number of fixation sequences, which allows for easier comparisons.
- A transition matrix displays the probability that visual attention (fixation) will transition from one area of interest to another.

CHAPTER 3

ORIGINAL PROPOSAL SUMMARY AND METHODS

Proposal Summary

The proposed project will investigate whether the graph format used to convey outcome estimate information about rt-PA treatment affects the way that older adults process that information and whether it affects their decision process as they make a hypothetical decision about rt-PA treatment for a loved one. Eyetracking technology will be used in a between groups experiment and differences in visual attention by graph format will be compared.

Method

Participants

An initial sample of twenty-seven older adults (60 years and older) were recruited through telephone and email solicitation. Potential participants were identified via the SilverRoo database. The SilverRoo database consists of contact and demographic information for approximately 200 University of Missouri Kansas City (UMKC) alumni and their spouses who are over 60 years of age and have expressed a willingness to participate in research conducted by the Department of Psychology at UMKC. Participants were randomly assigned to one of three study conditions corresponding to the graph format used to present rt-PA risk/benefit information to them. Informed consent was obtained from all study participants, and each participant received fifteen dollars as compensation for their participation (see Appendix B).

Some analyses based on data from this initial group of participants were presented at the Cognitive Aging Conference (Poirier et al., 2014; see Appendix C). Subsequently 18 additional participants were recruited and tested in the same protocol. The final sample was size *n*= 45.

Measures

Demographic Questionnaire – This basic demographic survey includes items such as participant age, level of education, a brief medical history, and a household income estimate (see Appendix D).

Working With Numbers (Numeracy) – Numeracy is a key person-level characteristic that can affect health literacy and health decision quality. This measure, which has been used in other health literacy studies, consists of six questions that require a basic understanding of ratios and percentages. Total possible score = six (Brown et al., 2011) (see Appendix E).

Working With Graphs (Graphicacy) – According to Carpenter and Shah (1998) and many others, "individual differences in graphic knowledge should play as large a role in the comprehension process as does variation in the properties of the graph itself" (p. 97). This 13-question measure assesses an individual's ability to comprehend and use information presented in different graph formats. It was developed for and has been used in prior health literacy and decision aid research. Total possible score = 13 (Galesic & Garcia-Retamero, 2011) (see Appendix F).

Modified Decisional Conflict Scale (DCS) – Level of decisional conflict is a key outcome measure in this project. Participants were asked to complete a modified version of the DCS after having made a decision about whether or not they would like their family member to be treated with rt-PA in the event of a stroke. This 13-question version of the DCS was used to assess participant level of decisional conflict across three subscales:

Decision Uncertainty, Factors Contributing to Uncertainty, and Perceived Efficacy in Decision Making (Katapodi et al., 2011) (see Appendix G).

rt-PA Comprehension/Recall Questionnaire – Study participants were asked nine multiple choice questions regarding the risks and benefits of using rt-PA. For example:

1. What is the primary risk of tPA? a) Arrhythmia b) Second stroke c) Paralysis d) Bleeding
2. What is your chance of bleeding with tPA? a) Less than 2% b) Approximately 6% chance c) Approximately 9% d) Greater than 11% chance (see Appendix H).

Stroke rt-PA Decision Aid Presentation – Text-based and graphic representations of risk benefit information related to the use of rt-PA (from RESOLVE) were presented to study participants on a 17-inch computer monitor in the form of a PowerPoint presentation. Three different presentations of 50 slides were developed for this study. All three presentations included the same slides with white text on a black background and differed only in the graph format used to depict the risks and benefits of using rt-PA. All three RESOLVE graphs were presented in gray scale on a black background.

Equipment

Eyetracker 6000 – An Applied Sciences Laboratories remote eye tracker was used to monitor gaze fixations while the participants were viewing the rt-PA graphs. The eye tracker samples eye position 60 times per second with an accuracy rating of 0.5° visual angle and provides a continuous stream of data including eye position (X-Y coordinates) and pupil diameter.

Eye tracking booth – The eye-tracking booth is a sound-attenuated room that contains a table and chair, computer monitor, and a Applied Science Laboratories D-6 optics module. On a table in front of the participant is a 17-inch computer monitor. The eye-tracking camera is situated in a custom-designed harness just below the computer monitor. The eye-tracking camera receives instruction from and sends data to two computers that are located outside of the booth.

GazeTracker™ software – GazeTracker software by Eyetellect was used for stimulus presentation, data acquisition, and some preliminary data analysis. In data acquisition mode, GazeTracker converts eye location data provided by the eye tracker into a series of fixations mapped onto to areas of interest (AOIs) corresponding to different graphic elements. Fixations are defined as a minimum of two sampled eye positions occurring with a fixation diameter of 30 pixels with a minimum duration of 100 msec. Fixation order can then be used to establish individual scan paths. See Figures 1.1-1.3 for the iHITTS study RESOLVE graphs with visible AOIs.

Digital audio recorder – An Olympus WS-100 digital voice recorder was used to record participants' verbal protocol (a) regarding whether or not they would like rt-PA administered to a family member in the event of a stroke; (b) their answers on the decisional conflict scale; (c) their responses to the comprehension questions; and (d) their choice of preferred graph format.

Procedure

Participants came to the SilverRoo Lab, located on the campus of the University of Missouri-Kansas City, where basic study procedures were explained to them and informed consent was obtained. Once consent was obtained, they were asked to complete a Demographic Questionnaire. A research team member was present throughout part one of the study to answer any questions and to assist participants as needed. This portion of the study took approximately 15 minutes to complete.

At this point, the participant was seated in the eye tracking booth and the digital audio recorder was set to record. The operation of the eye tracker was explained and a calibration routine was run with the participant. The calibration routine involved having the participant look at each dot in a 9-dot array on the computer screen while the computer recorded the position of their eye.

Next the participant was shown one of three rt-PA decision aid presentations depending on which study condition they were randomly assigned to (A, B or C). All three presentations were exactly the same except for the graph format in which example outcome estimates of disability and bleeding were presented: (A) bar, (B) stacked, or (C) iconic. Participants were instructed to read the information presented to them for comprehension and at their normal reading pace, and they were also told that they would be asked questions about the material later so they might want to read some information more than once.

Following the presentation of some general information about stroke and rt-PA, each participant was asked to (1) imagine a scenario in which a member of their family had suffered a stroke, (2) study a graph which presented estimates of their loved ones' expected level of disability and likelihood of bleeding with and without rt-PA treatment, (3) make a decision about rt-PA treatment, and (4) to tell the researcher when they had made their decision. Once the participant indicated that they had come to a decision, the slide was advanced to a second identical slide and participants were asked to explain that decision. This was done to separate eye movement data during the decision phase from eye movements in the explanation phase of data collection. The presentation duration of each slide was controlled by the participant. Total reading/viewing time for each slide and gaze durations to the presented materials were recorded including reading time and fixations while the participant considered their decision regarding rt-PA and immediately following that decision as they explained their reasoning for the decision.

After explaining their decision, participants were administered computerized versions of both the Decisional Conflict Scale and the rt-PA Comprehension/Recall Quiz. Directly following the Comprehension/Recall Quiz, they were shown each of the three graph types (bar, stacked and iconic) and asked which graph format they preferred. Participants were allowed to study each graph individually for as long as they wanted, and were then shown all three graphs together and asked to indicate which graph format they preferred. Presentation order was controlled so that when they were allowed to study the graphs individually, the second graph each participant viewed was always the same graph they had seen in the first part of the study. This portion of the study required approximately 20 minutes to complete.

At this point, the eye tracking portion of the experiment was complete and the participant was asked to exit the eye tracking booth. Study personnel then administered paper and pencil versions of the Working with Numbers numeracy measure and the Working with Graphs graphicacy measure. Once these two measures were completed, participants were debriefed and given $15 as compensation for their participation. This final portion of the study required approximately 15 minutes to complete.

The eyetracking data from iHITTS will be analyzed using “eyePatterns” software (West et al., 2006). EyePatterns is a free software package that runs in a Java environment. According to the software authors, “With eyePatterns, unknown and specified patterns can be found through discovery and pattern matching, respectively" (West et al., 2006, p. 153). It was designed specifically to aid researchers to discover and compare patterns in eye movements and visual fixation sequences within and across experimental groups of subjects. EyePatterns can be used to calculate the frequency of transitions from visual fixations in one area of interest to another and can determine mathematical similarity between fixation sequences using both the Levenshtein and Needleman Wunsch algorithms. Local alignment functions further enhance the software package's power by allowing for the discovery and comparison of closely related subsequences within a larger sequence. This is interesting because scan patterns that are dissimilar when analyzed using global similarity metrics may actually contain important undetected local similarities. "This may occur because the sequences are of different lengths or may contain the same subsequences, or cycles, which appear at different locations for each sequence" (West et al., 2006, p. 152).

CHAPTER 4

ANALYSES

iHITTS Hypotheses and Analysis Plan

Three graphs created for the RESOLVE study were assessed. All three graphs presented the same personalized outcome probabilities information related to the use of rt-PA, each in a different graph format. The goal was to identify the format that older adults preferred and the format which produced the best understanding of risk/benefit probabilities in order to promote informed decision-making.

To this end a between-subjects design was utilized to compare the effect of the three graph formats [(A) bar graph, (B) stacked graph, or (C) iconic graph, (see Figures 1.1-1.3)] on two dependent variables: memory of risk-related information and level of decisional conflict in regard to a hypothetical decision about whether or not to have a family member receive rt-PA therapy. The results of this analysis are reported and discussed in Chapter 1.

Primary Hypotheses

Graph comprehension is contingent upon reader ability and the complexity, construction and format of the graph being read (Kosslyn, 1989). Graph format may affect information encoding and memory of risk-related information.

1. If graph format affects memory of risk information about rt-PA, then memory accuracy as measured by the rt-PA Comprehension/Recall Questionnaire (see Appendix H) will differ across the three groups. The results of this analysis are reported and discussed in Chapter 1.

Decision tools are intended to facilitate decision-making and minimize decisional conflict. They most often provide decision makers with risk/benefit information pertaining to their decision in the form of a graph. However, there are many different graph formats that can be utilized to convey this information and like comprehension and memory, decisional conflict may be affected by the complexity, construction, and format of the graph being read.

2. If graph format affects iHITTS study participants' level of decisional conflict, then decisional conflict as measured by the Decisional Conflict Scale (see Appendix G) should differ across the three groups. A one-way analysis of variance with three levels (graph type) will be employed to examine group differences in decisional conflict. The results of this analysis are reported and discussed in Chapter 1.

Secondary Inquiries

We are interested in which graph format older adults will say they like best and whether that preference is related to other measured variables such as years of education, numeracy, and graphicacy.

1. To investigate potential relationships between graph preference and these variables, three preference groups will be created (bar, stacked, iconic), and parallel one-way analyses of variance will be conducted to test whether years of education, numeracy, and/or graphicacy differ significantly by graph format preferred. Graph preference and numeracy and graphicacy differences are reported in Chapter 1. Preference analyses related to education, numeracy, and graphicacy were not conducted because study participants were not significantly different in relation to these variables.

It is possible that memory of risk-related information and decisional conflict may be related to graph preference; i.e., information may be remembered better when presented in the format preferred by the graph viewer.

2. To investigate whether memory of risk-related information is related to graph preference, two groups will be created. The first group will consist of data from participants who viewed the RESOLVE graph for which they indicated a preference, and the second group will consist of data from participants who viewed a RESOLVE graph other than the one for which they indicated a preference. An independent samples t-test will be conducted to establish whether memory of risk-related information differs significantly between the two groups. This analysis was not conducted because an insufficient number of study participants reported having studied the graph format they most preferred.

Decisional conflict may vary when older adults make their decision about rt-PA while viewing the RESOLVE graph for which they indicated a preference versus one that is less preferred.

3. To investigate whether decisional conflict is related to graph preference, two groups will again be created. The first group will consist of data from participants who viewed the graph for which they indicated a preference (prior to making a decision about rt-PA) and the second group will consist of data from participants who viewed a graph other than the one for which they indicated a preference. An independent samples t-test will be conducted to establish whether memory of risk-related information differs significantly between the two groups. This analysis was not conducted because an insufficient number of study participants reported having studied the graph format they most preferred.

Format may affect the amount of time participants spend viewing a graph prior to announcing a decision about whether or not to have a family member treated with rt-PA. Increased viewing time may be associated with comprehension difficulty or it may reflect the importance of the information being viewed.

4. To establish whether there are significant differences in viewing time as a function of graph format, a one-way analysis of variance with three levels will be conducted to compare mean viewing times by graph format (bar, stacked, iconic). The results of this analysis are reported and discussed in Chapter 1.

5. If the amount of time participants spend fixating critical information areas differs by graph type, then percent of total viewing time spent fixating critical information areas will differ by graph type. A series of one-way analyses of variance was conducted to compare the percent of time spent fixating each critical area of interest by graph format (bar, stacked, iconic). The results of this analysis are reported and discussed in Chapter 1.

Exploratory Hypotheses

There is evidence that suggests that eye movements are guided by both task-relevant goals and salient stimulus characteristics. Given this evidence:

1. It is hypothesized that the consensus fixation sequences of iHITTS study participants will differ as a function of which graph they viewed while making their decision about rt-PA. To investigate this hypothesis consensus fixation sequences will be calculated for each graph format based on iHITTS participants' scan paths as they viewed the RESOLVE graphs and deliberated over their rt-PA decision. Pairwise comparisons of these consensus fixation sequence will be carried out and Levenshtein distance scores and Needleman Wunsch sequence alignment scores will be tabulated utilizing eyePatterns software. Consensus fixation sequences are expected to differ substantially by graph format given that they are essentially a distillation of the fixation patterns they represent. If two or more AOIs in the consensus fixation sequence derived from one of the graphs are ordered differently than those from another graph, this would suggest that the overall fixation

patterns of iHITTS participants differed as a function of which graph they viewed while making their decision about rt-PA. A visual inspection of consensus scan paths was conducted and results of this analysis are reported in Chapter 1.

2. It is hypothesized that the consensus fixation sequences derived from the scan paths of iHITTS participants who viewed the same graph format, while making their decision about rt-PA, will be more similar than those derived from scan paths of iHITTS participants who viewed a different graph format while making the same decision. This exploratory hypothesis will be investigated as follows:

The scan paths generated by participants within each graph format will be divided into two groups via random selection and consensus fixation sequences will be calculated for each group. In this way two consensus sequences will be produced for each graph format; each sequence representing half of the scan paths from a given graph format. Pairwise similarity/dissimilarity analysis of all six consensus sequences will be carried out. Levenshtein distance scores and Needleman Wunsch sequence alignment scores will be tabulated with eyePatterns software. Levenshtein distance scores are expected to be lower and Needleman Wunsch sequence alignment scores higher for pairs of sequences derived from the same graph as compared to pairs of sequences derived from different graph formats. This pattern of findings would suggest that the overall fixation patterns of iHITTS participants were more similar within graph formats and will further support the notion that the overall fixation patterns of iHITTS participants differed as a function of which graph they viewed while making their decision about rt-PA. This analysis was not conducted as it was deemed to be beyond the scope of the current project.

As Glaholt and Reingold (2011) suggested, encoding is not expected to be "uniform across decision alternatives, meaning highly relevant alternatives are processed more deeply, and poor alternatives are processed to a lesser extent, or possibly even excluded from further processing" (p. 141). In fact, decision makers may exclude all but a subset of the most relevant information to the decision at hand (Glaholt & Reingold). Howard and Jagdish (1969) described the subset of alternatives that are under closest consideration during decision making as a consideration set. Shi, Wedel, and Pieters (2013) found that the number of alternatives in a consideration set varies between one and four alternatives.

3. It was hypothesized that the eye tracking record would provide evidence that iHITTS participants constructed a decision set consisting of the 2-4 most decision-relevant pieces of information from the RESOLVE graphs.

To investigate this hypothesis the scan path sequences generated by iHITTS participants will be scrutinized. If a pattern emerges such that 2-4 AOIs are fixated with greater frequency than all other AOIs and the frequency of fixation to these AOIs increases with temporal proximity to the decision announcement regarding rt-PA use, then these 2-4 AOIs will be assumed to comprise a decision set. The results of this analysis are reported and discussed in Chapter 1.

The last few fixations in multi-alternative and preference decisions tend to be concentrated on the chosen item (Glaholt & Reingold, 2011). It is probable that in a binary decision which involves the assessment of multiple attribute levels (disability levels in this case) and their probabilities, the last few fixations prior to announcing a decision will be focused on the most relevant information, outcomes or attributes (from the decision-maker's perspective).

4. It is hypothesized that a study participant's consensus fixation sequences during a verbal explanation of their decision would be similar to their fixation patterns during the last five seconds prior to their decision announcement. This exploratory hypothesis would be investigated as follows:

To investigate this hypothesis, pairwise comparisons will be made of the fixation sequences iHITTS study participants generated during the last five seconds prior to giving a verbal explanation of their rt-PA decision (Study sequence) and their fixation sequences during their decision explanation (Decision sequence). Given that the number of fixations each participant made during the last five seconds prior to their rt-PA announcement is expected to vary and in light of the methodological difficulties of comparing fixation sequences of varying lengths; each participant's study sequence will be compared to a decision sequence comprised of the same number of fixations. Additionally, decision sequences will begin from the first instance of fixation location matching that of the first fixation from their study sequence. So for example, if study sequence (1) is compared to decision sequence (2), the first two AOIs in the decision sequence are ignored in the calculation of consensus sequences.

Study sequence (each letter represents a different AOI): a_b_c_d_e_f_g, (1)

Decision sequence: (each letter represents a different AOI): c_d_a_b_c_d_c_f_g, (2)

This analysis was not conducted as it was deemed to be beyond the scope of the current project.

5. Further, it is hypothesized that during a verbal explanation of their decision iHITTS study participants will fixate first and most frequently on the AOIs identified as compromising their decision set. This analysis was not conducted because of difficulty

isolating the visual fixations associated with the participant's explanations of their decision. Researchers were also speaking during a portion of this time, making data interpretation uncertain.

Although it is assumed that decision makers employ heuristics when making decisions, it may not be possible to discern the specific heuristics that were utilized to make a decision from a decision maker's pattern of visual fixation. Overall, it may be easier to use fixation patterns to distinguish decision stages such as those outlined in the proposed stage model of visual decision-making rather than to identify the use of specific heuristics.

It is hypothesized that data from the eye tracking record will reveal biases in fixation order, frequency, and duration that suggest that iHITTS participants engaged in a decision process similar to that described by the proposed stage model. This analysis was not conducted, and there is no mention of the proposed stage model in Chapter 1. This analysis was deemed to be beyond the scope of the current project.

APPENDIX A

LITERATURE REVIEW FIGURES

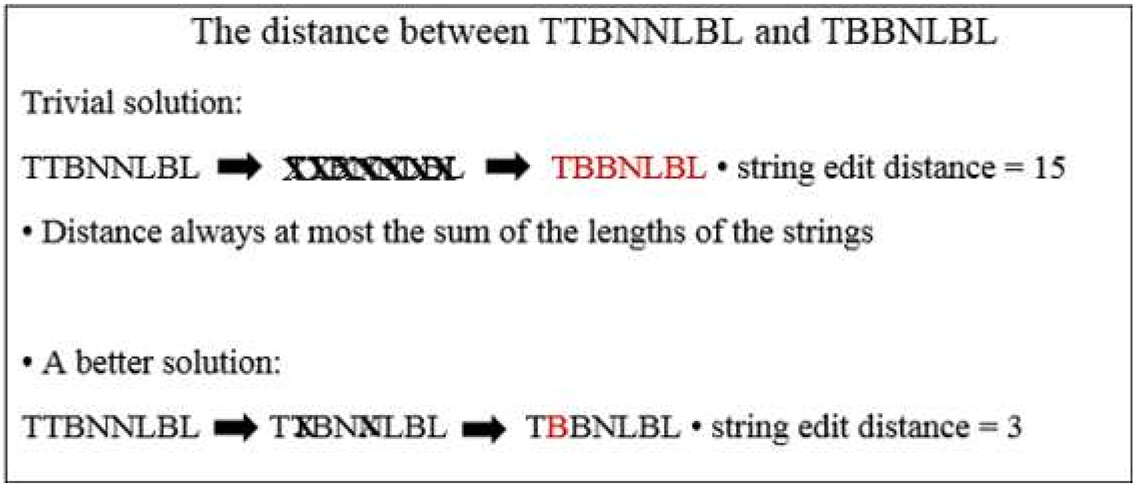


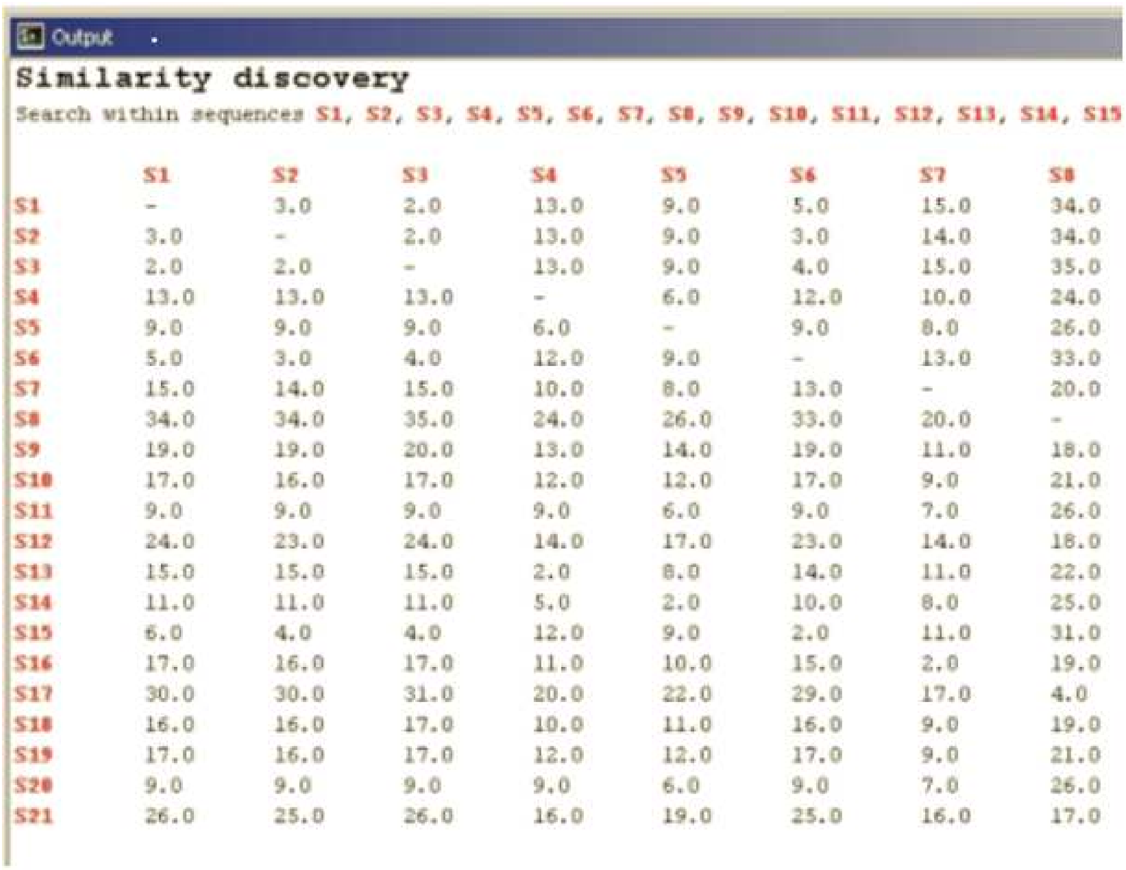
Figure A1. String Edit Distance. Adapted from Raiha (2006)

	N	L	B	F	*
N	1	-1	-1	-1	0
L	-1	1	-1	-1	0
B	-1	-1	1	-1	0
F	-1	-1	-1	1	0
*	0	0	0	0	0

Figure A2. This is the basic Needleman-Wunsch algorithm. NWA alignment scores can be modified by choosing different penalty values for the three alignment operations. For instance, if there are two AOIs that are close together on the stimulus, it may make sense to make a mismatch between those areas cost less than a mismatch between AOIs that are spatially distant.

```
BLLBLBNLLBLBNLLFBLFB---LFFLLLLFFFNB
|||| ||| ||||| |||||   ||||||||||||
BLLBNBNLFBLBNLFFBLFBNNNLFFLLLLFFFNB
```

Figure A3. An example of sequence alignment where the first four characters are a match, the fifth character is a mismatch, and there are three gaps. Reprinted from West et al. (2006).



Output

Similarity discovery

Search within sequences S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11, S12, S13, S14, S15

	S1	S2	S3	S4	S5	S6	S7	S8
S1	-	3.0	2.0	13.0	9.0	5.0	15.0	34.0
S2	3.0	-	2.0	13.0	9.0	3.0	14.0	34.0
S3	2.0	2.0	-	13.0	9.0	4.0	15.0	35.0
S4	13.0	13.0	13.0	-	6.0	12.0	10.0	24.0
S5	9.0	9.0	9.0	6.0	-	9.0	8.0	26.0
S6	5.0	3.0	4.0	12.0	9.0	-	13.0	33.0
S7	15.0	14.0	15.0	10.0	8.0	13.0	-	20.0
S8	34.0	34.0	35.0	24.0	26.0	33.0	20.0	-
S9	19.0	19.0	20.0	13.0	14.0	19.0	11.0	18.0
S10	17.0	16.0	17.0	12.0	12.0	17.0	9.0	21.0
S11	9.0	9.0	9.0	9.0	6.0	9.0	7.0	26.0
S12	24.0	23.0	24.0	14.0	17.0	23.0	14.0	18.0
S13	15.0	15.0	15.0	2.0	8.0	14.0	11.0	22.0
S14	11.0	11.0	11.0	5.0	2.0	10.0	8.0	25.0
S15	6.0	4.0	4.0	12.0	9.0	2.0	11.0	31.0
S16	17.0	16.0	17.0	11.0	10.0	15.0	2.0	19.0
S17	30.0	30.0	31.0	20.0	22.0	29.0	17.0	4.0
S18	16.0	16.0	17.0	10.0	11.0	16.0	9.0	19.0
S19	17.0	16.0	17.0	12.0	12.0	17.0	9.0	21.0
S20	9.0	9.0	9.0	9.0	6.0	9.0	7.0	26.0
S21	26.0	25.0	26.0	16.0	19.0	25.0	16.0	17.0

Figure A4. A portion of a distance score matrix, created with eyePatterns software, which displays Levenshtein distance scores between scan paths S1-S21. Because the Levenshtein distance method was used here, low scores indicate greater similarity. The same table could be constructed using the Needleman-Wunsch algorithm, in which case higher scores would be indicative of greater dissimilarity.

Transition matrix

	A	B	C	D	E	F
A	0	3	0	2	2	1
	0.00%	33.34%	0.00%	22.23%	22.23%	11.12%
	0.0%C	23.08%C	0.0%C	13.34%C	15.39%C	6.67%C
B	4	0	0	3	0	0
	33.34%	0.00%	0.00%	25.00%	0.00%	0.00%
	44.45%C	0.0%C	0.0%C	20.0%C	0.0%C	0.0%C
C	2	5	0	5	1	0
	13.34%	33.34%	0.00%	33.34%	6.67%	0.00%
	22.23%C	38.47%C	0.0%C	33.34%C	7.7%C	0.0%C
D	1	2	0	0	6	2
	6.67%	13.34%	0.00%	0.00%	40.00%	13.34%
	11.12%C	15.39%C	0.0%C	0.0%C	46.16%C	13.34%C
E	0	0	0	0	0	3
	0.00%	0.00%	0.00%	0.00%	0.00%	25.00%
	0.0%C	0.0%C	0.0%C	0.0%C	0.0%C	20.0%C
F	0	1	0	2	1	0
	0.00%	8.34%	0.00%	16.67%	8.34%	0.00%
	0.0%C	7.7%C	0.0%C	13.34%C	7.7%C	0.0%C

Figure A5. A portion of a transition matrix showing transition probabilities.

APPENDIX B

INFORMED CONSENT

University of Missouri-Kansas City
SilverRoo Research Laboratory

Informed Consent: Improving Health Information about Stroke Treatments

Introduction

As a healthy older adult, you are being invited to participate in a research study to examine eye movements made during reading health information. This study will take place at the UMKC SilverRoo Lab, located in Cherry Hall on the UMKC campus. Cherry Hall is located at 5030 Cherry Street. You will be one of approximately 24 participants taking part in this research project.

Purpose

The purpose of this study is to learn how people read and understand health information. In this case you will be reading information about tissue plasminogen activator, commonly called tPA and its use with people who have had a stroke. You will also look at pictures and graphs that are designed to illustrate the risks and benefits of using tPA. It is hoped that the information gained in this study will help us better communicate information about tPA so that the reader can fully understand risks and benefits of the medicine.

Procedure

Your participation in this study will involve the following:

1. Completing 3 short questionnaires. The first asks some questions about you – birthdate, occupation, health conditions, education. A second questionnaire focuses on your reading activities, such as how much you read and what kinds of things you read. And finally, you will complete a questionnaire that assesses your knowledge of health information.

2. Reading informational material about the use of tPA following stroke. The information will be presented on a computer screen while a camera records the movement of my eyes. You will be asked to read at your own pace during this task, but you will need to pay attention to the meaning of the material because you will be given a short quiz after reading all of the slides.

3. Describing out loud the meaning of information presented as pictures or graphs. These pictures or graphs show the risks and benefits of being treated with tPA. You will be asked to describe your understanding of the information, and we will record your voice using a digital tape recorder. Later we will listen to what you have said and analyze how you have described the graphs. Because your description is an important part of this study, you must agree to this recording in order to participate.

4. Completing a multiple choice comprehension test on the information presented in the reading portion of the study.

5. Completing a brief measure of your math knowledge, and a brief measure of your knowledge about how to interpret a graph.

You may ask for rest periods at any time during the testing period. The entire session is expected to last approximately 60 minutes.

Voluntary Participation

Participation in this study is voluntary at all times. You may choose not to answer any of the questions that make you feel uncomfortable. You may choose to not participate or to withdraw your participation at any time. Deciding not to participate or choosing to leave the study will not result in any penalty or affect your ability to participate in other programs through UMKC or the SilverRoo Program.

Risks

There are no known risks to you for participating in this study.

Benefits

You will not benefit directly by participating in this study. Our society may benefit from the findings of this study, by allowing health care workers and researchers to better understand how people use visual information and make decisions.

Costs and Payments

There is no cost to you for participating in this experiment. You will receive a payment of $15 for participating in the study even if you chose not to complete the testing.

Confidentiality

Dr. McDowd will take measures to protect the confidentiality of the information you provide in this study. For example, the data collected about you will be labeled with an anonymous ID code, including the digital file of your voice describing the pictures and graphs. The file that links this code to your name and personal information will be kept in a locked cabinet. The coded data will be entered into a password protected computer so that only Dr. McDowd's research team will have access. In addition, access to the computer itself will be protected by a password.

The audio recording of your voice describing the graphs will be stored on a password-protected computer. The same anonymous ID code that is used for the other tasks will be used to label the computer audio files. It will not be linked to your name. A member of the research team will listen to the recording and write down everything you say. Once we have a written version of your descriptions of the graphs, we will delete the electronic version from our recorder and from our computer.

While every effort will be made to keep confidential all of the information you complete and share, it cannot be absolutely guaranteed. Individuals from the University of Missouri-Kansas City Institutional Review Board (a committee that reviews and approves research studies), Research Protections Program, and Federal regulatory agencies may look at records related to this study for quality improvement and regulatory functions. Your identity will not be provided on any of the measures. Also, if the information obtained in this study is presented at professional conferences or published in journals, you will not be identified in any way.

<u>In Case of Injury</u>

The University of Missouri-Kansas City appreciates the participation of people who help it carry out its function of developing knowledge through research. A copy of this consent form will be provided for you, and should you have any questions about the study that you are participating in you are encouraged to call Joan McDowd, the investigator, at (816) 235-2490.

Although it is not the University's policy to compensate or provide medical treatment for persons who participate in studies, if you think you have been harmed as a result of participating in this study, please call the IRB Administrator of UMKC's Social Sciences Institutional Review Board at 816-235-5927.

<u>Questions</u>

If you have any questions about this study at any time, you may contact Dr. McDowd at the University of Missouri-Kansas City, Department of Psychology, Kansas City, MO 64110 or you may phone her at 816-235-2490, or e-mail her at mcdowdj@umkc.edu and she will be happy to answer any of your questions. If you have any questions about your rights as a research participant please contact the Administrative Office of the Social Science Institutional Review Board (SSIRB) at 816 235-5927 or UMKC-SSIRB at umkcssirb@umkc.edu

Consent

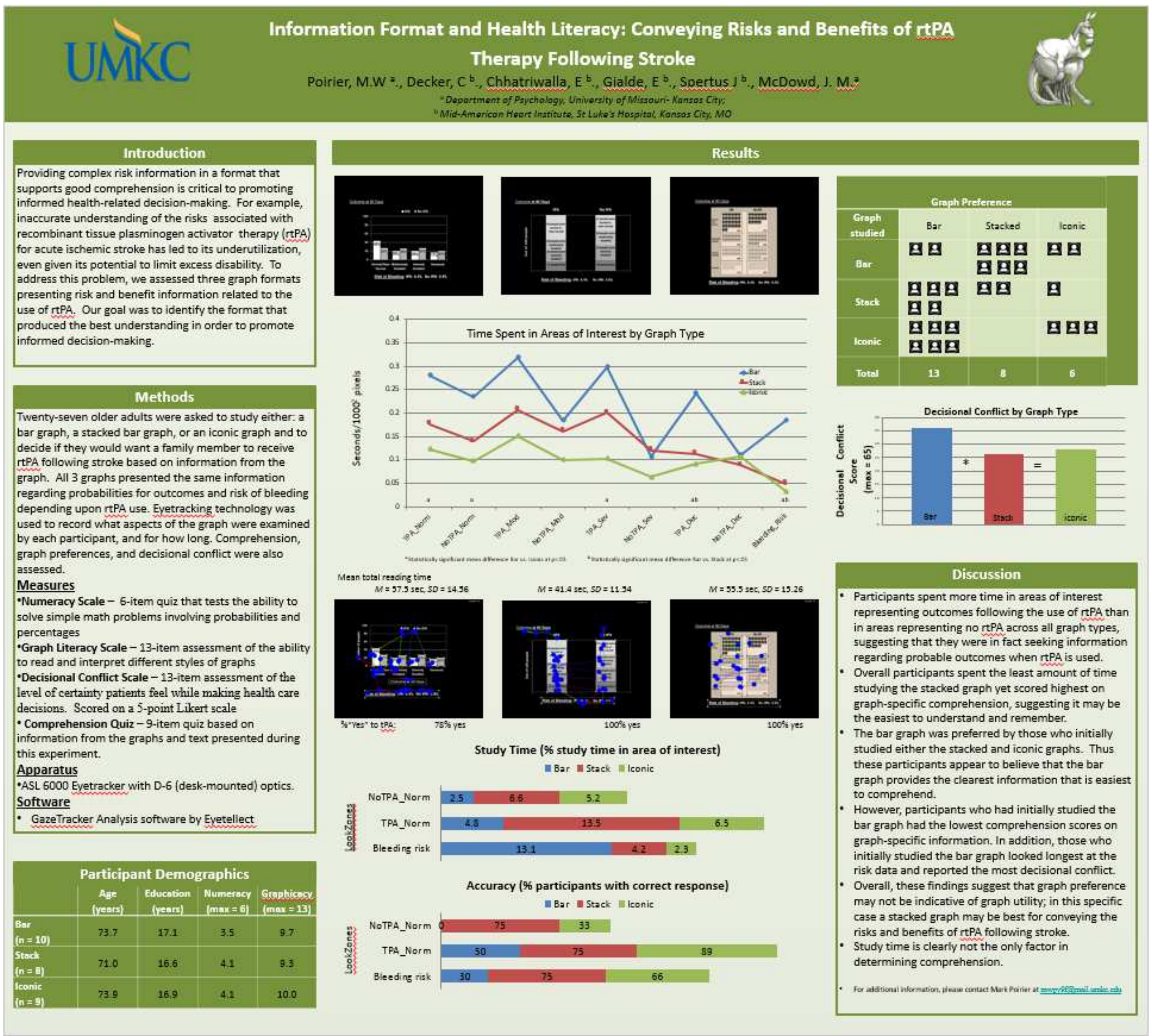
By signing your name below, you are indicating that (1) you have read this form, (2) you agree to participate in this study, (3) you have received a copy of this consent form, and (4) you agree to have the information you share in the study be used for the stated research purposes.

(Signature of Participant)	(Print Name)	(Date)

(Signature of Investigator)	(Print Name)	(Date)

APPENDIX C

COGNITIVE AGING CONFERENCE POSTER



APPENDIX D

iHIITS PARTICIPANT DEMOGRAPHICS

1. Sex: (_____) 1= Male / 2= Female

2. What is your date of birth? _ _ / _ _ / _ _ _ _

3. How old are you? Age:_________

4. What is your marital status? (_____)
   1 = Never married
   2= Cohabitating
   3 = Separated
   4 = Divorced
   5 = Widowed
   6 = Married
   7 = Civil Union

5. How far did you get in school? (_____)
   1= Grade School
   2= High School
   3= Some College
   4= college degree
   5= Post Graduate

6. Which of the following best describes your ethnicity? (_____)
   1 = White
   2=Black/ African-American (not Hispanic)
   3 = Hispanic
   4 = American Indian
   5 = Asian
   6 =Hawaiian/ Pacific Islander
   7 = Other:______________

7. What is your current living situation? (_____)
   1=Alone in apartment
   2=Alone in house
   3=With S/O in apartment
   4=With S/O in house

7b. If with S/O, who? (_____)
   1=Spouse/Partner
   2=Child (ren)
   3= Other family
   4= Roommate
   5= Other non-relative

8. Have you lived any place else during the past year? (including hospital) (_____)
   1=No 2=Yes

9. What is your current employment status now? (_____)
   1 = Full time (30 hrs/wk or more paid)
   2 = Part time (less than 30 hrs paid)
   3 = Not currently employed, not retired
   4 = Homemaker (not paid)
   5= Retired

10. Which category best describes your yearly household income before taxes? ________

    Do not give me the dollar amount, just give me the category. Include all income received from employment, social security, support from children or other family, welfare, Aid to Families with Dependent Children (AFDC), bank interest, retirement accounts, rental property, investments, etc.

    1 = Less than $5000
    2 = $5000 - $9,999
    3 = $10,000 - $14,999
    4 = $15,000 - $19,999
    8 = $50,000 - $59,999
    9 = $60,000 - $69,999
    10 = $70,000 - $79,999
    11 = $80,000 - $99,999

5 = $20,000 - $29,999
6 = $30,000 - $39,999
7 = $40,000 - $49,999

12 = $100,00 or more
13 = Refused
14 = Don't know

11. Is there anyone who handles your money for you? (_____) 1=No 2= Yes

12. Do you wear or need glasses? (_____) 1=No 2= Yes

13. Do you wear or need a hearing aid? (_____) 1=No 2= Yes

14. Have you experienced multiple strokes? (_____) 1=No (GO TO Q. 24) 2= Yes

15. Date of latest stroke? _ _ / _ _ / _ _ _ _

16. Date of first stroke? _ _ / _ _ / _ _ _ _

17. What side did you experience the stroke? (_____) 1=Left 2= Right

18. Handedness? (_____) 1=Left 2= Right

Medical History: Tell me about your medical history.

19. Cardiac Disease (_____) 1=No 2= Yes
20. Diabetes Type I Type II (_____) 1=No 2= Yes
21. High Cholesterol (_____) 1=No 2= Yes
22. Hypertension (_____) 1=No 2= Yes
23. Head Injury (_____) 1=No 2= Yes
24. Neurological illness (e.g., Stroke, MS, Parkinson's, Seizures, Brain Tumor) (_____) 1=No 2= Yes
25. Headaches (_____) 1=No 2= Yes
26. Cancer (_____) 1=No 2= Yes
27. Other:____
____
____
____

28. Psychiatric History: Have you ever been diagnosed with a mental disorder? (_____) 1=No 2= Yes

29. If yes what diagnosis? ______________________________________
____
____

30. Which category best describes your yearly household income before taxes? _______

Do not give me the dollar amount, just give me the category. Include all income received from employment, social security, support from children or other family, welfare, Aid to Families with Dependent Children (AFDC), bank interest, retirement accounts, rental property, investments, etc.

1 = Less than $5000	8 = $50,000 - $59,999
2 = $5000 - $9,999	9 = $60,000 - $69,999
3 = $10,000 - $14,999	10 = $70,000 - $79,999
4 = $15,000 - $19,999	11 = $80,000 - $99,999
5 = $20,000 - $29,999	12 = $100,00 or more
6 = $30,000 - $39,999	13 = Refused
7 = $40,000 - $49,999	14 = Don't know

31. Is there anyone who handles your money for you? (_____) 1=No 2= Yes

32. Do you wear or need glasses? (_____) 1=No 2= Yes

33. Do you wear or need a hearing aid? (_____) 1=No 2= Yes

34. Have you experienced multiple strokes? (_____) 1=No (GO TO Q. 24) 2= Yes

35. Date of latest stroke? _ _ / _ _ / _ _ _ _

36. Date of first stroke? _ _ / _ _ / _ _ _ _

37. What side did you experience the stroke? (_____) 1=Left 2= Right

38. Handedness? (_____) 1=Left 2= Right

APPENDIX E

WORKING WITH NUMBERS

1) Imagine that you flip a coin 100 times. About how many times will the coin come up heads?

2) After flipping a coin 10 times you have counted 7 heads and 3 tails. What is the chance that your next flip will come up heads?

3) 100 people have entered the Spring City Run. Seventy percent of the runners will finish the race. Of the 100 people who entered the race, how many will finish?

4) In the Washington School raffle 5 people out of 100 who entered will win a prize. What percentage (%) of people who entered will win a prize?

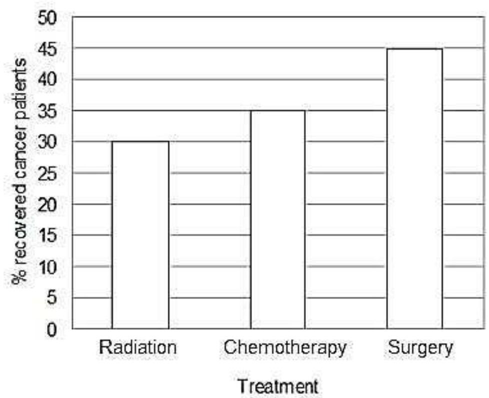
5) How much is one percent of 1000?

6) One is what percent of 1000?

APPENDIX F

WORKING WITH GRAPHS

Here is some information about cancer therapies.



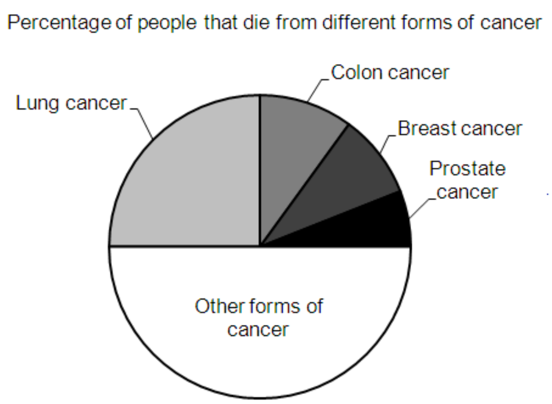
1. What percentage of patients recovered after chemotherapy?

_______________%

2. What is the difference between the percentage of patients who recovered after a surgery and the percentage of patients who recovered after radiation therapy?

_______________%

Here is some information about different forms of cancer.



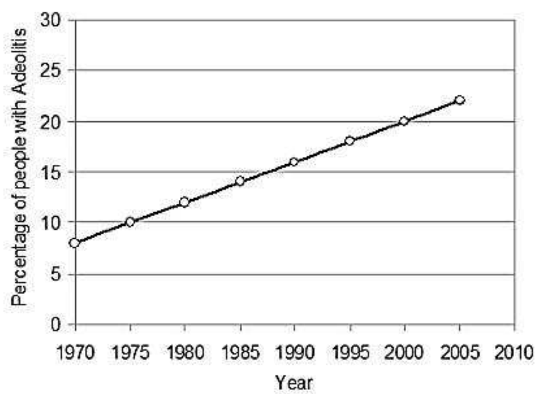
3. Of all the people who die from cancer, approximately what percentage dies from lung cancer?

____

4. Approximately what percentage of people who die from cancer die from colon cancer, breast cancer, and prostate cancer taken together?

_________%

Here is some information about an imaginary disease called Adeolitis.



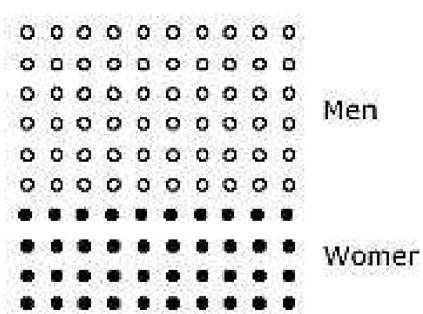
5. Approximately what percentage of people had Adeolitis in the year 2000?

_______________%

6. When was the increase in the percentage of people with Adeolitis higher?

1) From 1975 to 1980
2) From 2000 to 2005
3) Increase was the same in both intervals
4) Don't know

The following figure shows the number of men and women among patients with disease X.
The total number of circles is 100.



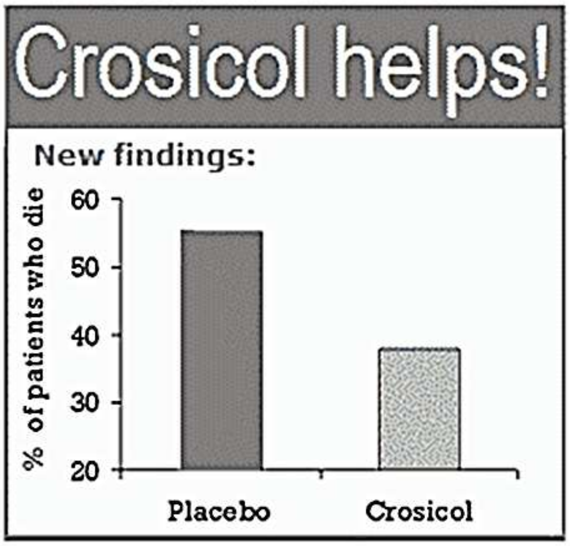
8. Of 100 patients with disease X, how many are women?

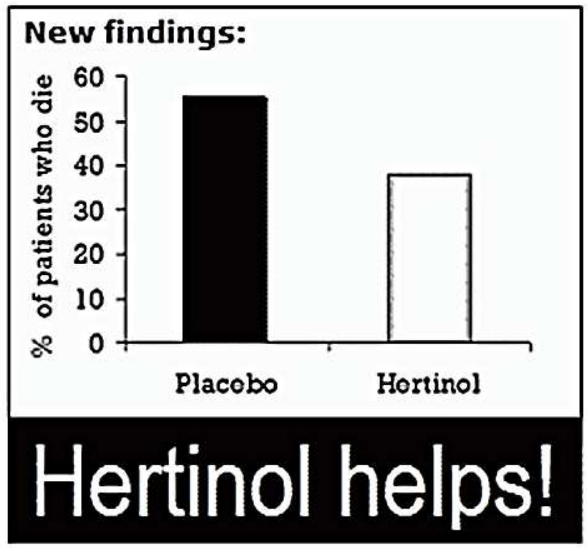
_______________women

9. How many more men than women are there among 100 patients with disease X?

_______________ men

In a magazine you see two advertisements, one on page 5 and another on page 12. Each is for a different drug for treating heart disease, and each includes a graph showing the effectiveness of the drug compared to a placebo (sugar pill).

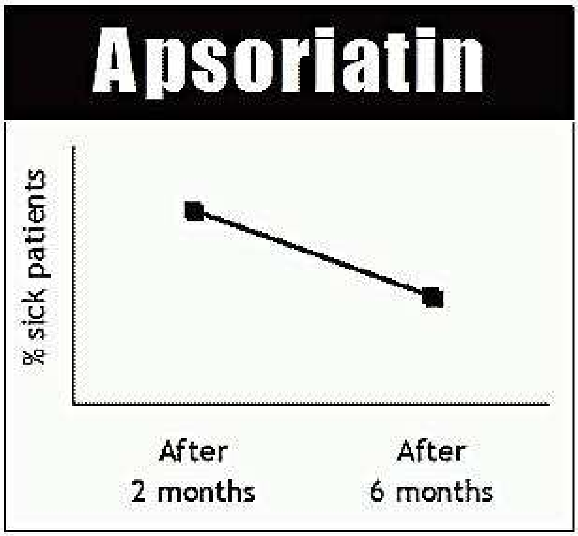


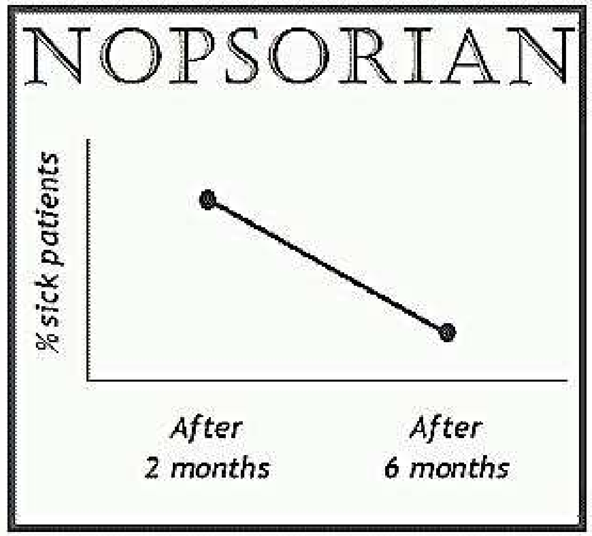


10. Compared to the placebo, which treatment leads to a larger decrease in the patients who die?

1) Crosicol
2) Hertinol
3) They are equal
4) Can't say

In a newspaper you see two advertisements, one on page 15 and another on page 17. Each is for a different treatment of psoriasis, and each includes a graph showing the effectiveness of the treatment over time.

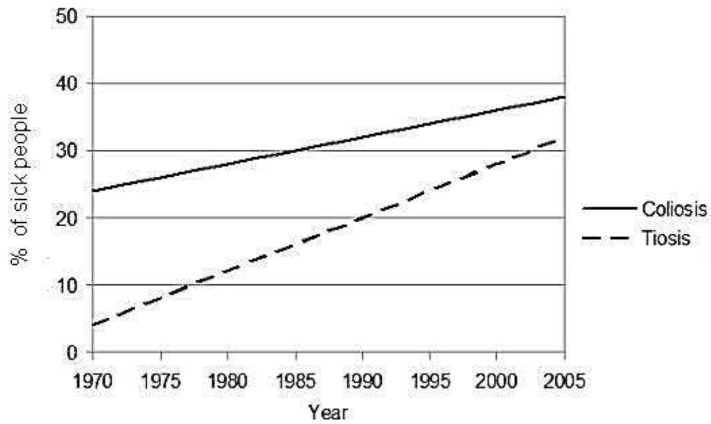




11. Which of the treatments contributes to a larger decrease in the percentage of sick patients?

1) Apsoriatin
2) Nopsorian
3) They are equal
4) Can’t say

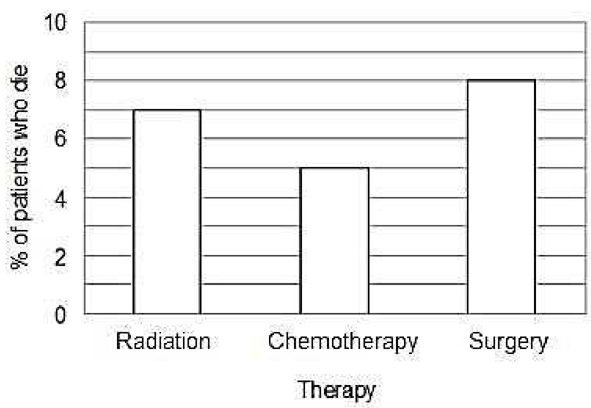
Here is some information about the imaginary diseases Coliosis and Tiosis.



12. Between 1980 and 1990, which disease had a higher increase in the percentage of people affected?

1) Coliosis
2) Tiosis
3) The increase was equal
4) Can't say

Here is some information about cancer therapies



13. What is the percentage of cancer patients who die after chemotherapy?

________________%

APPENDIX G

DECISIONAL CONFLICT SCALE

Decision Uncertainty subscale

1. This decision is easy for me to make
2. I'm unsure what to do in this decision
3. It is clear what choice is best for me

Factors Contributing to Uncertainty subscale

4. I'm aware of the choices I have to (specify purpose)
5. I feel I know the benefits of this (specify purpose)
6. I feel I know the risks and side effects of (specify purpose)
7. I know how important the benefits are to me in this decision
8. I know how important the risks and side effects are to me in this decision
9. It is hard to decide if the benefits are more important to me than the risks, or if the risks are more important than the benefits
10. I need more advice and information about the choices

Perceived Efficacy in Decision Making subscale

11. I feel I have made an informed choice
12. My decision shows what is important to me
13. I am satisfied with my decision

Likert Scale

5 = strongly disagree, 4 = disagree, 3 = neither agree nor disagree, 2= agree, 1 = strongly agree - All Q's except 2,9,10
1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree - Q's 2,9,10

APPENDIX H

COMPREHENSION QUIZ

1. An ischemic stroke happens when….
    a) You have a heart attack
    b) An artery to your brain becomes blocked
    c) You have a concussion
    d) You have a severe headache

2. The penumbra is…
    a) An artery in the brain
    b) A part of the heart
    c) A type of stroke
    d) The brain area around a stroke

3. tPA is…
    a) A government organization
    b) A type of stroke
    c) A clot-dissolving medicine
    d) A medical device

4. tPA must be used…
    a) Within 1 ½ hour of a stroke
    b) Within 1 day of a stroke
    c) Within 1 week of a stroke
    d) Within 4 ½ hours of a stroke

5. If choosing to receive tPA following stroke…
    a) You will have a good outcome
    b) You may have a good outcome
    c) You will not have a good outcome
    d) You will recover completely

6. What is the primary risk of tPA?
    a) Arrhythmia
    b) Second stroke
    c) Paralysis
    d) Bleeding

7. What is your chance of bleeding with tPA
    a) Less than 2%
    b) Approximately 6% chance
    c) Approximately 9%
    d) Greater than 11% chance

8. Out of 100 people, how many were normal or near-normal after getting tPA?
    a) 27
    b) 43
    c) 16
    d) 23

9. Out of 100 people, how many were normal or near-normal who did not get tPA?
    a) 27
    b) 43
    c) 16
    d) 23

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VITA

Mark William Poirier was born August 6, 1972, in Montreal, Quebec. At the age of five, he moved to Calgary, Alberta, where he completed his primary and secondary education. He began attending the University of Missouri-Kansas City in the fall of 2009 and graduated in 2012 with a major in Psychology.

Mark began his graduate training in 2013 when he was accepted to the Experimental Health Psychology Ph.D. Program at the University of Missouri-Kansas City, where he conducted research under the guidance of Joan McDowd Ph.D.

Mark is a member of the Society for Psychphysiological Research, the Association for Psychological Science, and a past member of the American Psychological Association (Div. 20): Adult Development and Aging.