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Visualizing Data Quality Metadata for Decision Support: A Prototype and Evaluation

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ABSTRACT

Data quality (DQ) metadata is the set of quality measurements associated with the data. Literature has demonstrated that the provision of DQ metadata can improve decision performance. However, it also showed that DQ metadata can overload decision-makers and negatively affect decision performance. In this paper, we examine a technique for reducing this overload by using visualization. Recognizing that visualization shifts the burden of absorbing DQ metadata to the perceptual capacity of the decision maker, we argue that it will reduce cognitive load. We theorize that decision-makers can hence absorb DQ metadata more easily. Decision performance will improve even when DQ metadata is provided. We describe the visual interface for visualizing data and DQ metadata and describe an experiment to test the impacts of visualizing DQ metadata on decision outcome. The results of this study offer insights for the design of decision support systems and the provision of DQ metadata.

Keywords

Data Quality, Data Quality Metadata, Visualization, Decision Performance, Decision Support.

INTRODUCTION

Poor decision quality has been attributed to poor data quality (e. g., Redman, 1996; Ford and Goia, 2000). One way of managing data quality for decision-support is to provide decision-makers with ***data quality metadata (DQ metadata)***, *data that describes the quality of the data,* along with the data used. Decision-makers can gauge quality in the context of the task and accordingly, lean more on the better quality data (Shankaranarayanan and Cai, 2005). Studies have shown that providing DQ metadata can change decision outcomes (Fisher, Chengalur-Smith and Ballou, 2003). Recent research has shown that providing DQ metadata can improve decision outcomes in structured, data-driven decision-tasks (Shankaranarayanan, Zhu and Cai 2008). The research also shows that the positive effect of DQ metadata can be offset by the extra processing it demands. Integrating DQ metadata into the decision process requires additional cognitive resources. This overload may leave less cognitive resource for the decision task itself and decision performance may degrade. The positive impact of providing DQ metadata outweighs its negative impact only when decision-makers have the ability to integrate and process DQ metadata. However, research has not examined the circumstances under which decision-makers can effectively use DQ metadata.

Our objective in this paper is to examine if visualization can improve the decision maker's ability to integrate DQ metadata. Research has shown that visualizing data in graphs can relieve cognitive load by supporting perceptual inferences (Larkin and Simon, 1987). We posit that visualization can facilitate the integration of DQ metadata into the decision process. We first build a theoretical foundation and define a set of hypotheses that theorize our notion – visually presenting DQ metadata will have a larger positive impact on decision performance when compared with presenting it textually. We design and create a decision-support interface for visualizing the data used in the decision task *and* associated DQ metadata. Using an experimental setting, we evaluate our visualization interface by examining its impact on decision outcome. This understanding can guide the design of systems that support decision-making with DQ metadata. It also helps determine if investing in special purpose visual interfaces for presenting DQ metadata are necessary.

Decision-making can be individual and organizational (Eisenhardt and Zbaracki 1992). In this study, we focus on individual decision-making. Thompson's model (1967) classifies decision-tasks into four types – analytical, judgmental, bargaining, and inspiration - based on whether the decision-objective and the means to produce results are known. *Our focus is on analytical decision-tasks in which the means to produce results and the decision-objective are both known.* According to Nutt (1984), analytical tasks often involve large amounts of data to draw inferences. Eisenhardt and Zbaracki (1992) state that analytical tasks belong to rational decisions in which decision makers enter decision situations with known objectives, gather appropriate information, develop a set of alternative actions, and select the optimal one. The process adopted in rational decision making is structured (Keen and Scott Morton, 1978). *We adopt structured, analytical decision-tasks to evaluate the impact of visualizing DQ metadata*. It has been shown that the task complexity can be increased by the presence of DQ metadata in such data-driven tasks (Shankaranarayanan et al., 2008). So, these are ideal for examining the effects of visualizing DQ metadata. Also, such structured tasks have an optimal solution, making objective evaluation of decision performance feasible.

Task complexity impacts decision process and outcome (Eisenhardt and Zbaracki 1992). Though complexity has many factors including psychological and personal characteristics, *we focus on the objective task characteristics*. These include factors such as the number of alternatives, number of attributes and time pressure (Payne, Bettman, and Johnson, 1993). In this study, *we focus on structured decision-tasks*, which typically involve a number of alternatives and each alternative can be evaluated on a group of criteria (attributes). To find the optimal solution, decision makers must consider the matrix of alternatives and evaluation criteria. The elements of matrix are called "knowledge states" in the decision space. The number of elements in the matrix is used as an indicator of task complexity (Payne et al. 1993). *We adopt this definition for defining task complexity. Based on the number of elements in our decision space we classify our tasks as simple and complex tasks*.

In the remainder of this paper, we first develop a theoretical foundation by drawing from literature on visualization and literature on decision-support and information representation. Using this theory, we then define our hypotheses. We describe our experimental setting including the prototype decision-support interface for visualizing data and DQ metadata. Experimental results are then presented and analyzed. We conclude by reiterating the contributions and highlighting the benefits of this research.

THEORETICAL FOUNDATION AND HYPOTHESES

Recent work shows that when decision-makers have the ability to process DQ metadata, this does improve decision performance (Shankaranarayanan et al., 2008). It further shows that adding DQ metadata increases task complexity. This effect was moderated by decision experience. The conclusions from this study are: (1) adding DQ metadata increases task complexity – a simple task may become complex and a complex task, significantly more complex. (2) When the task remains simple even with DQ metadata, experience does not play a significant role. The decision performance was comparable between experienced and less-experienced decision makers. Both were able to integrate DQ metadata into the decision process. (3) Decision-makers with DQ metadata performed better than decision-makers without DQ metadata. Thus, decision performance is improved by the provision of DQ metadata. (4) When the task is complex (with DQ metadata), experienced decision-makers were able to integrate DQ metadata and achieve superior performance compared with less-experienced decision-makers. Among less-experienced decision-makers, those that did not receive DQ metadata exhibited superior performance (comparable time, higher task accuracy), compared with those that received DQ metadata. Hence, for complex tasks, DQ metadata degraded performance for less experienced decision-makers. Experienced decision-makers with DQ metadata took more time (with better task accuracy) compared with experienced decision-makers without DQ metadata. Hence, even for experienced decision-makers, DQ metadata lowers decision performance, in terms of time.

Given that decision-making stands to gain from DQ metadata only when the DQ metadata does not cause information overload, this paper examines whether visualization can reduce the information overload. The paper extends the above described research by examining how to help decision-makers integrate DQ metadata into the decision process. One method is to reduce the cognitive effort – decision-makers may then have spare cognitive capacity to effectively integrate DQ metadata. As Todd and Benbasat (1999) stated, decision-support systems must extend the cognitive limit of the decision-maker. As human eyes can perceive different visual cues simultaneously, visualizing data in graphs may relieve cognitive load by supporting perceptual inferences (Larkin and Simon, 1987). Literature in information systems defines visualization as "*the use of computer-supported, interactive, visual representations of abstract data to amplify cognition*" (Card et al., 1999). Human memory structure theory (Ware, 2000) explains how visualization reduces cognitive effort in information processing. It categorizes human memory into three layers: iconic, working and long-term memory. The iconic memory prefers input data in visual format and can capture multiple visual cues simultaneously, meaning, more channels to transfer input data into working memory. Moreover, this perceptual stage can detect certain visual patterns without having to go through the more resource-intensive cognitive process. In working memory, visual cues can be used to speed up internal data processing by reducing the cognitive load of mental reasoning. When the cognitive load is high, perceptual processes facilitate more efficient processing (Vessey and Galetta, 1991). Research has stated that visualization can help when task complexity increases as decision-makers use visual heuristics to simplify the tasks (Smelcer and Carmel, 1997; Speier, Vessey, and Valacich, 2003). *In this paper, we examine the effects of visualizing DQ metadata*. Metadata visualization has been studied in the context of large documents and digital libraries (e.g., Wise et al., 1995) and in the context of uncertain metadata in Geographic Information Systems (Malczewski, 1999).

We designed an interface to visually present DQ metadata to decision-makers. This interface, SPIDEV (Special Purpose Interface for Decision Evaluation and Visualization), is part of a prototype system that allows decision-makers to visualize both data and associated DQ metadata. For brevity, the prototype is not discussed further. The metaphor used in this research is the spoke-wheel, a modification of Kiviat chart (Morris 1974). Anderson and Dror (2001) used the metaphor to assist decision-makers in multi-criteria decision-making. Each spoke represents a criterion in the decision task. The length of the spoke represents the value of the criterion. To make the display more comparable, the length representing the criterion value is standardized - the maximum length is the radius of the wheel. For instance, say, we are evaluating MP3 players using five criteria – *Size, Appearance, Sound-quality, Price and Functionality*. Each player is assigned a rating (numerical value) along each of the criteria – the value represents how that player is rated along that criteria (this may be obtained from, say, Consumer Reports, a more reliable source, or from web-communities – a relatively less reliable source). Figure 1 is our visual representation of these parameters for a specific (say, Player-1) MP3 player. The player is rated 9 (on a 10-point scale) on "Size". The length of the spoke representing "Size" is 90% of the radius of the wheel. "Appearance" is rated 7 and the length of its spoke is 70% of the radius. The interface also represents DQ metadata with the data. Pipino et al. (2002) specify the quality may be measured over multiple dimensions such as timeliness and accuracy. There may be one value for each dimension or a single, overall quality value may be used. Quality is specified as a percentage or fraction. In this study, we use a single quality dimension and its value is specified as a fraction. In our example, let us assume that the quality (say, reliability) of each rating may vary, depending on the source of the data. If the data quality associated with the rating for "Size" is 0.5, then, a second spoke is laid over the first spoke corresponding to "Size". This spoke represents the *same data weighted for its data quality* (rating = 9; DQ (metadata) = 0.5, quality-weighted rating = 4.5) and the length is now 45% of the radius of the spoke wheel. Cleveland and McGill (1984) have found the human eye to be more accurate in reading grouped bars that have a fixed common baseline and hence we have overlaid the two spokes (data and quality-weighted data). The visualization may be further enhanced by using colors. If data quality is poor, the quality-weighted spoke is colored red, green if good, and yellow for quality that is in-between. What is good and unacceptable may be specified by the user.

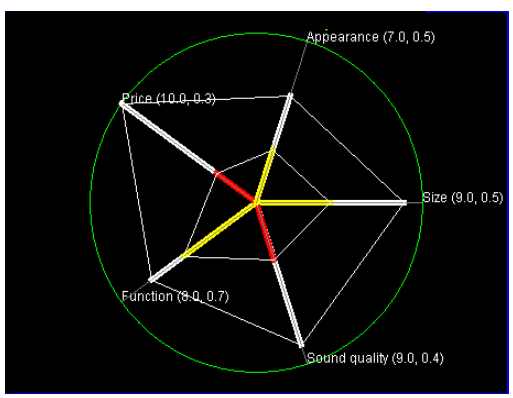


Figure 1: Metaphor for Visualizing Data and DQ Metadata

Visualizing data allows perceptual processing which typically needs less effort and consumes less time. Moreover, people often can identify patterns through visual aids, but fail to do so when viewing tables and numbers (Larkin and Simon, 1987). If data and metadata were presented textually, it is difficult for users to differentiate the metadata and data and to create a mental model of the relationship between the two. Visualizing both could provide visual cues and heuristics and consequently benefit decision performance. We expect the visual representation of data and DQ metadata can reduce cognitive load in a structured decision environment. Therefore, we propose:

Hypothesis 1: Decision makers with visualization will have lower perceived mental demand in solving decision-tasks compared to decision makers with textual representation.

If visualization can reduce the mental demand required to integrate DQ metadata into the decision process, decision makers will be able to utilize DQ metadata faster and better. Consequently, all other things being equal, decision makers need not sacrifice decision accuracy in the trade-off between cognitive effort and decision accuracy (Payne et al. 1993). We expect visualization to improve decision making evidenced by higher objective decision accuracy. We also expect a more efficient decision process evidenced by faster decision time. Hence,

Hypothesis 2: Decision makers with visualization will achieve better decision-making accuracy compared to decision makers with textual representation.

Hypothesis 3: Decision makers with visualization will have shorter decision-times compared to decision makers with textual representation.

A subjective performance variable included in this research is the perceived confidence in the decision. Self-efficacy beliefs are important in Social Cognitive Theory (Bandura, 1986). If a person feels they are capable of achieving the goal, then they are likely to work harder and consequently more likely to succeed compared to a person who is not confident. Therefore, if the presence of DQ metadata impacts the decision makers' confidence, it may indirectly impact decision performance. If a decision maker believes that the DQ metadata provides a more complete picture of the decision task, s/he is likely to have a higher self-efficacy and consequently a higher confidence in the decision. On the contrary, if the decision maker thinks that the DQ metadata increases the decision-making difficulty, s/he may have a lower self-efficacy and a lower confidence. In the absence of a strong theoretical base to support the positive or negative impacts of DQ metadata on subjective decision performance, we propose:

Hypothesis 4: Decision makers with visualization will have higher perceived confidence in decisions compared to decision makers with textual representation.

EXPERIMENTAL SETTING

The visual interface used is part of a prototype system for decision-support. The system offers a wide range of functionality, permitting users to define decision criteria, colors, and the constraints for the solution space. It also permits users to use sliders to vary the decision criteria and perform "what-if" analyses. The textual interface presented to the control group did not have such features. To eliminate bias or confounding effects, we stripped the prototype of its added functionality and used only the visual presentation interface in our experiment.

We developed a set of 11 different decision-tasks. All tasks required users to evaluate and choose an MP3 player from a set of four, based on Size, Appearance, Functionality, Sound quality, and Price. Rating (value) was provided for each criterion along with the reliability (quality) of each rating. MP3 players are popular gadgets with a variety of makes/models – each task was differentiated from others by the combination of the players in the task, ratings, and/or reliability values. Using the prototype tool, visual representations (figure 2a) and tabular textual representations (figure 2b) of the candidate MP3 players with the criteria and associated DQ metadata were generated, for each of the tasks. A special purpose application to serve the representations associated with each task, one at a time, was created. This could also record objective measurements such as the time spent on each task. The control group accessed the application with textual interfaces and the experimental group accessed the application with visual interfaces. Both were pre-tested using 10 doctoral students (avg. work experience of 8 years) from a business school. From the pilot, we were able to identify and correct minor issues in the descriptions, decision-tasks and questionnaires. The pilot also provided face validity for the constructs used in the experiment.

Research subjects were recruited from a pool of second-year MBA students enrolled in a major university. A total 52 subjects participated. Among them, two did not finish the task and/or the following survey. Therefore, the final effective sample size was 50 (12 females and 38 males; avg. age = 28 years; avg. work experience = 4.8 years; avg. management work experience = 1.8 years). We controlled for individual differences to reduce possible confounding effects. Subjects were randomly assigned to the treatment (26 subjects, 6 females) or control group (24 subjects, 6 females). From demographic data, we did not find any significant differences in terms of gender, age, working experience, management working experience, previous experience with MP3 players, computer skills and math skills between subjects in the two groups. The experiment was conducted in a controlled lab setting. Each subject was assigned with a computer preloaded with the appropriate application.

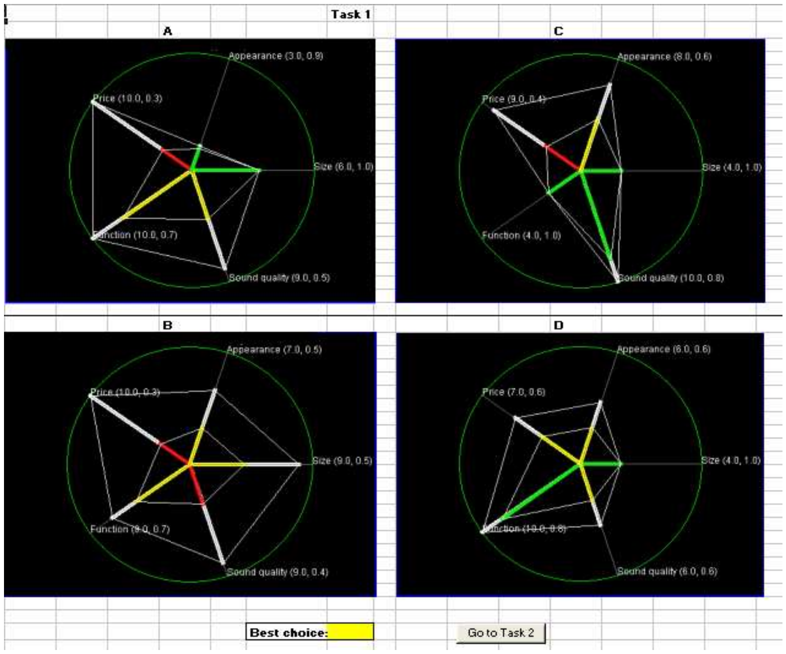


Figure 2a: Sample Visual Interface

Task 1

A

Criterion	*Rating*	*Reliability*
Size	6	1
Sound quality	9	0.5
Function	10	0.7
Price	10	0.3
Appearance	3	0.9

C

Criterion	*Rating*	*Reliability*
Size	4	1
Sound quality	10	0.8
Function	4	1
Price	9	0.4
Appearance	8	0.6

B

Criterion	*Rating*	*Reliability*
Size	9	0.5
Sound quality	9	0.4
Function	8	0.7
Price	10	0.3
Appearance	7	0.5

D

Criterion	*Rating*	*Reliability*
Size	4	1
Sound quality	6	0.6
Function	10	0.8
Price	7	0.6
Appearance	6	0.6

Best choice:

Go to task 2

Figure 2b: Sample Textual Interface

At the start, the experiment coordinator clearly explained the procedures and protocols. Subjects were asked to fill a short demographic survey. Then experiment coordinator demonstrated two sample tasks to explain how to interpret the decision task and how to integrate DQ metadata into the task. During the demo, sufficient time was allocated to solicit and answer questions. We thus ensured that all subjects were on the same ground and understood the accepted method for solving the structured task (conformant with rational structured decisions). Subjects then started and worked independently. The tasks were presented in the same sequence to both groups. The next task appeared only when the subject completed or skipped the current task. The application recorded the solution for and the time spent on each task. There was a time limit for solving those tasks (determined from the pilot test). After the experiment, subjects were asked to complete a survey capturing their experiences and perceptions. We ensured involvement in the decision-tasks by offering cash rewards for top performers. Based on perceptual data, the average involvement was 5.21 on 7-point Likert-scale, significantly higher than the neutral score of 4 with $p < 0.001$. No significant difference in involvement scores was found between the two groups.

RESULTS, ANALYSES, AND DISCUSSION

We adopted most of our constructs (see table 1) from literature to ensure high construct validity. Perceived task complexity was measured using items such as "The task was complex for me", "The task was difficult to understand" – each measured on a 1(Strongly Disagree) -7 (Strongly Agree) Likert-scale. These items were used in previous studies by the authors and were pre-tested and refined. All constructs achieved good reliability (Cronbach's Alpha greater than 0.7) and discriminant validity, supported by confirmatory factor analysis.

Constructs	Cronbach's Alpha
Mental Demand/Cognitive effort (from Speier and Morris 2003)	0.7132
Mental effort deployed by subject in making decision/ Involvement (from Lilien et al., 2004, Marketing scales handbook)	0.7457
Perceived DQ metadata usefulness (from Venkatesh and Davis 2000, Lilien et al., 2004)	0.8247
Perceived Task Complexity	0.7465
Perceived Confidence (from Fisher et al. 2003)	N.A.

Table 1: Constructs and Discriminant Validity

To avoid bias in comparing decision performance across groups, we identified whether subjects in experimental group had the same perception of decision task complexity as subjects in control group. We also checked whether subjects in both groups had the same level of involvement. After running the independent sample T-test, we found no significant differences in the measures of "Perceived Task Complexity" and "Involvement" between treatment and control groups. Hence, in this experiment, using visualized or textual formats did not affect the subjects' perceptions of the task complexity. Further, there was no significant difference in involvement, between groups.

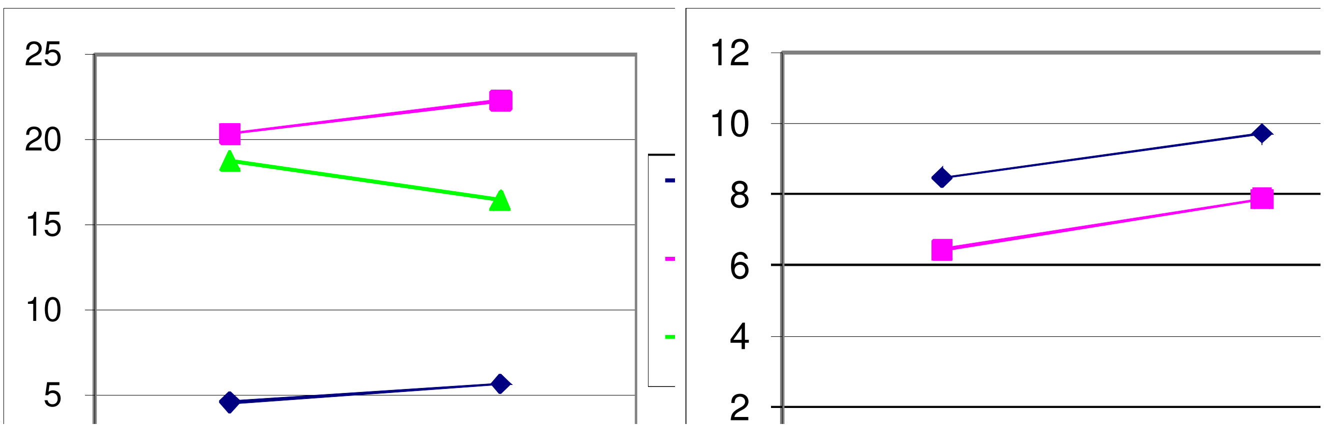
We first examined the subjective responses to analyze perceptions *dealing with hypotheses 1 and 4*. Decision makers with visual representation reported lower mental demand in solving decision-tasks (16.44 vs. 18.77, significant with $p < 0.05$) than decision makers with textual representation. This data supports our *hypothesis 1*. Decision makers with visual representation also reported higher perceived confidence (5.68 vs. 4.59 on 7-point Likert-scale, significant with $p < 0.01$) compared with decision makers with textual representation. This supports *hypothesis 4*. There was no significant difference is the perceived usefulness of DQ metadata between the control group (5.67 on a 7-point scale) and the experimental group (5.73).

Examining objective decision-making effectiveness, subjects with visual representation of DQ metadata made more correct decisions (7.85 vs. 6.42, significant with $p < 0.05$) than subjects with textual representation. Moreover, subjects with visual representation achieved higher decision accuracy (81.2% vs. 76.1%, marginally significant at $p < 0.1$) than the subjects with text. These results *support, albeit weakly, hypothesis 2*. In solving a set of 11 decision-tasks, the average time spent overall is almost identical across subjects with textual representation and subjects with visual representation (519.92 seconds vs. 519.58 seconds). Considering decision-making efficiency, subjects with visual representation completed significantly more number of tasks (9.69 vs. 8.46, significant with $p < 0.05$) than those with textual representation. In terms of average time per task, subjects with visual representation spent less time on each task than subjects with textual representation (59.02 vs. 69.09 seconds, marginally significant at $p < 0.1$). For the same set of tasks and with the same time restrictions, compared to the subjects with textual representation, the subjects with visual representation solved more tasks, had solutions that were more accurate, and had a higher percentage of accurate solutions. *This supports hypothesis 3*. These results are summarized in table 2. Figures 3a and 3b graphically represent the perceptual and the objective measurements respectively.

Meanwhile, there were no significant differences regarding subjects' perceptions along "easy to understand", "easy to use", "effort to comprehend the meaning", and "time to comprehend the meaning" between textual and visual representation of DQ metadata. (When eye-balled, the numbers indicate that the textual interface appeared easier than the visual– this may switch if the volume of data is larger or if a simpler visual metaphor is used). Subjects using visual representation also perceived the visual interface positively - the average score of "perceived ease of understanding" of the visual representation is 4.65 on 7-point Likert-scale, higher than the neutral score of 4 with $p < 0.05$; the average score of "perceived ease of use" of the visual representation is 4.68 on 7-point Likert-scale, higher than the neutral score of 4 with $p < 0.01$. The perceptual measurements are presented in table 3.

	Textual Interface	Visual Interface	
Sample size	24	26	
Mental demand	18.77	16.44	Significant; p < 0.05
Perceived Confidence	4.59	5.68	Significant; p < 0.01
Perceived Performance	20.36	22.25	Significant; p < 0.05
Perceived Usefulness of DQ metadata	5.67	5.73	Not significant
Avg. total time (Sec)	519.92	519.58	Not significant
Avg. time per task (Sec)	69.09	59.02	Marginally significant; p < 0.1
Avg. tasks completed	8.46	9.69	Significant; p < 0.05
Avg. correct responses to tasks	6.42	7.85	Significant; p < 0.05
Task Accuracy in percentage	76.1%	81.2%	Marginally significant; p < 0.1

Table 2: Summary of findings



Figures 3a and 3b: Subjective and Objective Performances between groups

	DQ metadata in Text	DQ metadata in Visual	Significance
Easy to understand	*5.39*	4.65	None
Easy to use	5.09	4.68	None
Effort to comprehend the meaning	4.65	4.32	None
Time to comprehend the meaning	5.26	4.72	None

Table 3: Subjects' perceptions of the two interfaces

Our analyses largely support our theory. Examining subjects' perceptions, the perceived confidence in decisions is significantly higher for decision-makers using the visual interface. Perceived mental demand was significantly lower and perceived performance significantly higher for the decision-makers who visualized DQ metadata, though not as significant as perceived confidence. Further, there is no significant difference between the decision-makers' perceptions of ease-of-use, ease-of comprehension, and time-to-comprehend the two interfaces. This suggests that the visual representation did not have steep learning curve for first time users. After brief explanations in the demo session, subjects could understand the visual representation and use it efficiently. The interface was not a confounding factor. These observations lead us to believe that visualization of DQ metadata is beneficial in the context of structured decision-tasks. While this supports our theory, the objective measures provide some interesting insights. There is no significant difference in the total time spent on all the tasks by the two groups. There are two possible explanations. All participants were equally involved in the decision-tasks and took the allotted time to process the data and associated metadata to complete the tasks. This observation, combined with the fact that there was no significant differences in how the decision-makers perceived the two interfaces, leads us to believe that DQ metadata was systematically integrated into the decision process by both sets of decision-makers. This is further supported by the observation that the task accuracy percentage is only marginally better for decision-makers with the visualized interface and so is the average time spent on each task. This could be because the subjects were experienced and in neither group, the integration was restricted by cognitive capacity (confirming finding in Shankaranarayanan et al.,2008). However, the number of tasks completed and the number of correct responses indicate that the decision-makers who visualized data and associated metadata did have superior decision outcomes and processed more decision-tasks in the given time (higher task efficiency).

One limitation of this study is the sample size. We are extending it using a larger sample of decision-makers in a real-world setting. This would help improve generalizability and confirm our findings. Second, all 11 tasks were equally complex. Though sufficient to provide statistically significant differences in task efficiency, the total time and the time/task were very close across the two groups. The perceptions of the text and visual interfaces showed no differences. Future research should vary complexity within the set of tasks to gain insights into how the visual interface impacts task time and task efficiency. This will also offer insights into the perceptual differences between the two interfaces. A third direction is to examine the visual interface – the spoke-wheel is one of many metaphors. We should try and identify more effective metaphors for presenting DQ metadata. We believe this will be challenging as the effectiveness of metaphors may depend on the decision task.

CONCLUSION

In this paper, we presented a rationale and theoretical foundation for visualizing DQ metadata. From earlier research, we inferred that DQ metadata does positively impact decision performance and is useful. We further learned that when task complexity is high, DQ metadata can negatively impact decision outcomes by increasing the cognitive load on the decision-maker. The decision-maker often decides to give up cognitive effort and sacrifice decision accuracy. Using data visualization literature, we posited that visualization may reduce cognitive load. We developed a prototype system for decision-support which included a spoke wheel interface for visualizing data involved in the decision-task and associated DQ metadata. Using an experimental setting, we investigated whether the visual interface will permit a superior integration of DQ metadata compared with a textual interface, thus enhancing decision performance. The results of our experiment largely supported our theory and hypotheses.

The visual representation of DQ metadata can help communicate the meaning of DQ metadata to decision makers; reduce the mental demand to integrate DQ metadata into decision making, and consequently improve decision performance. The findings from this design and evaluation can guide the future development and implementation of visualization to provide DQ metadata to decision makers. It can facilitate the effective and efficient use of DQ metadata not only in simple tasks but also in more complex tasks. It also has the potential to minimize experience-gap: allow less experienced decision-makers to take advantage of DQ metadata, like more experienced decision makers.

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