Ensuring Positive Impact of Data Quality Metadata: Implications for Decision Support

Completed Research Paper

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Abstract (Required)

Organizations continue to manage poor quality data despite being aware of its negative impact on decision making. One effective way of addressing this situation is to inform decision-makers of the quality of the data they are using by providing data quality (DQ) metadata. However, despite its availability, not all decision-makers use DQ metadata. Further, when DQ metadata is included, the resulting dataset may be different from and significantly larger than the dataset created without DQ metadata. This potentially creates an information overload and the decision maker is conflicted about the use of DQ metadata. This paper demonstrates that decision-makers will use DQ metadata when a guideline about how DQ metadata should be used is provided. The paper also illustrates that variations in task complexity, work experience, and domain-specific experience interact. When guidance on how to use DQ metadata is provided the impact of DQ metadata on consensus among decision-makers depends on such interactions.

Keywords (Required)

Data Quality Metadata, Decision-Making, Structured Decision-Making, Task Complexity, Domain-specific experience

Introduction

The quality of data used in a decision impacts the quality of that decision (Eisenhardt and Zbaracki, 1992). As it is often cost ineffective to maintain high quality data, organizations continue to store and manage imperfect data (Madnick et al. 2009). One way to ameliorate the effects of imperfect data on decision outcome is to provide decision makers with data quality (DQ) metadata along with the data, to allow decision makers to gauge quality in the context of the decision task (Shankaranaryanan et al. 2003). The benefit of DQ metadata will be realized if two conditions are met: 1) decision-makers *use* DQ metadata when available and, 2) decision-makers achieve *superior decision outcomes* using DQ metadata. Research has shown that both these conditions are not satisfied when DQ metadata is provided. First, not everyone uses DQ metadata. Novice decision-makers were found to ignore DQ metadata when performing decision-tasks (Chengalur-Smith et al., 1999; Fisher et al., 2003). Second, it remains unclear if using of DQ metadata improves decision outcome. Expert decision-makers agreed less with each other on the right outcome with DQ metadata, than they did without it (Chengalur-Smith et al., 1999; Fisher et al., 2003).

We hence posit that providing DQ metadata alone is insufficient. Organizations should also provide guidance on how it should be used. Such guidance could address the above two issues. Novice decision-makers may not ignore DQ metadata because they now know how to use it. Experts may each use DQ metadata in some unique and different way. It is inevitable that each reaches a different conclusion. Guidance on how to use DQ metadata provides both a common and systematic way to use it and evaluate outcomes (which could still be different owing to other errors). Providing guidance on the use of data is typical in organizations (e. g., Philips and Polen, 2002). *However, how guidelines for using DQ metadata are created is not the focus of this paper*. Instead, this paper focuses on the interaction among DQ metadata, decision-tasks, and decision makers' experience when guidance on how to incorporate DQ metadata into the decision-task is provided. We found that providing guidance did encourage the use of

DQ metadata. Both the novices and experts used DQ metadata for all tasks with varying task complexities. But, providing guidance did not greatly improve the impact of DQ metadata on decision outcome. Indeed, such impact varied with the interaction between task complexity and decision-makers' experience. We also found that both the work experience and domain-related experience can mediate DQ metadata's impact on decision outcome. When guidance is provided, the inclusion of DQ metadata had a negative impact on outcome only among decision-makers without both types of experience, domain and work-related, and only for complex decision-tasks.

In this paper, we demonstrate that decision-makers will use DQ metadata when guidance on how to use it is provided, independent of the complexity of the task and the experience of the decision-maker. Further, this paper uncovers the situations when DQ metadata has a negative impact on outcome, even when guidance on how to use DQ metadata is offered. Our objective is to determine the circumstances under which DQ metadata positively impacts decision outcome. The contributions of this paper not only extend the literature in data quality management but also direct practitioners on how to ensure the positive impact of DQ metadata on decision outcomes. Today, social media data is extensively used to identify new marketing opportunities, improve customer satisfaction, and innovate with products and processes. Organizations, presumably, apply techniques to measure the reliability of the social media data and communicate measurements (e.g., ratings, likes) to decision-makers who range from novices who know social media to experienced hands that are less familiar with social media. This paper offers insights into how organizations should communicate the measurements to the different decision-makers.

We begin with a brief overview of the relevant literature to lay the foundation for our theoretical framework. We then describe our framework and explain how task complexity and experience impact the effect of DQ metadata on decision outcomes. We also present our hypotheses about decision outcomes derived from the model. We describe a controlled experiment used to validate our hypotheses. We finally present our findings and discuss the implications of DQ metadata for decision support.

Relevant Literature and Theoretical Framework

Our literature base covers concepts from DQ metadata and decision outcomes, decision tasks and task complexity, and the role of cognitive capacity and experience.

DQ metadata and decision outcome: Research has shown that providing DQ metadata may allow decision-makers to weight the data used in the decision task, based on its quality (Shankaranarayanan et al. 2003). DQ metadata, the quality indicator of the data, includes measurements along one or more data quality dimensions such as accuracy and completeness (Fisher et al. 2003). Decision-makers may ignore DQ metadata if they do not know how to use it or may use it in unique ways and hence reach different decision outcomes. Providing a guideline for integrating DQ metadata will allow decision-makers incorporate it and reduce the cognitive effort required to do so. Importantly, all decision makers will (at least theoretically) use it the same way and therefore it must be easier for them to agree on the outcome.

Literature has shown that provision of DQ metadata does impact the decision outcome (Chengalur-Smith et al. 1999, Fisher et al. 2003, Watts et al. 2009); however it has not shown that the impact is positive. The impact has been studied using two constructs (a) usage of metadata and (b) impact of DQ metadata on the outcome (Chengalur-Smith et al. 1999). Usage is measured using **complacency** and **consistency**. The former measures whether decision-makers change their top choices before and after integrating DQ metadata. The latter measures whether the overall ranking of all decision alternatives changes before and after integrating DQ metadata. We adopt the use of complacency and consistency to measure usage. Impact of DQ metadata on decision outcome is measured using **consensus** – whether decision makers agree with each other on the decision outcome, before and after integrating DQ metadata. Following this study, we adopt consensus to measure impact.

Decision task and task complexity: Our focus in this paper is on structured decision-tasks that use the analytical approach (from Nutt's (1998) classification of approaches to assess alternatives). Structured tasks have a set of decision variables. Decision-makers may weight each variable based on its relative importance for the task. There is also a set of decision alternatives. In such tasks, decision-makers enter the decision situation with known objectives, gather relevant data, identify the set of alternatives, and select the optimal (Eisenhardt and Zbaraki, 1992). Payne et al. (1993) suggest the use of two strategies to identify the optimal: weighted-additive and conjunctive. In the former, the decision-maker obtains the product of the value of each decision variable with its assigned weight and gets a total score by adding the products, for each alternative. The score (e.g., largest) is used to identify the optimal alternative. Using the latter strategy, the decision-maker sets a minimum range of acceptable values for each decision variable and rejects those alternatives for which the values are unacceptable. In this paper, we use structured, analytical decision-tasks and evaluate them using the weighted-additive strategy.

March and Simon (1958) identified factors that prevent decision-makers from reaching the optimal solution such as computational errors, limited cognitive capacity, and imperfect data. Payne et al. (1993) suggest that when the amount of task-related data surpasses the decision-maker's cognitive capacity, he will begin using heuristics to reduce complexity at the cost of decision outcome. We hence state that consensus level among decision-makers will decrease due to the above factors, especially, cognitive capacity that is affected by task complexity. Task complexity is determined by multiple factors – amount of task-related data, number of alternatives, availability of task-related data, and time (Payne et al. 1993). More decision alternatives and more decision variables lead to higher complexity (Wood, 1986). In this paper, task complexity is determined by the number of cells in the decision space represented by the matrix of decision variables and decision alternatives. Following earlier studies, we interpret decision-tasks with 20 or less cells to be simple and those with 40 or more to be complex (Campbell, 1988; Payne et al. 1993). When DQ metadata is included, the decision space is enlarged - it has two matrices– one formed by the variables and alternatives and the other by the variables and associated DQ metadata. Thus, complexity is increased by the inclusion of DQ metadata.

Experience and cognitive capacity: Cognitive capacity is the result of the interaction between working and long-term memories (Kieras and Meyer, 1997). When working memory capacity is exceeded, decision-makers resort to simplification strategies that decrease task performance (Streufert, 1973). Yufic and Sheridan (1996) state that long-term memory that holds data associated with experiences can extend the capacity of the working memory. In fact, it has been shown that with the same working memory capacity, a decision-maker with more experience can handle more data than a less-experienced decision-maker (Schoenfeld and Herrmann, 1982). In this paper, we focus on experience as proxy for working memory capacity – it is also easier to measure. We consider two types of experiences – work experience and domain-related experience. With more work-experience, decision-makers are better at organizing data, and capable of utilizing larger amounts of data (Mao and Benbasat, 2000). Hence decision-makers with more work experience can easily handle increased task-complexity due to DQ metadata.

Decision-makers with more domain-related experience are more knowledgeable and interested in the task domain (Tobias, 1994). This stimulates pleasant emotions towards the task resulting in deeper cognitive processing of the input data (Schiefele et al. 1992, Tobias, 1994). When handling the added complexity due to DQ metadata, decision-makers with more domain-related experience will be able to work with and use DQ metadata better than those with less domain-related experience.

Hypotheses and Experiment

Figure 1 presents a conceptual representation of our theoretical model. We posit that inexperienced decision-makers did not use DQ metadata (as established earlier by Fisher et al. (2003)), because they did not know how to use it. If guidelines were provided, they would use DQ metadata. Hence the top choice for optimal solution identified by decision-makers with DQ metadata will be different from those without DQ metadata. *H1: For the same task, when guidance on how to integrate DQ metadata is provided, decision-makers with DQ metadata will have a different choice for the optimal decision alternative than those without DQ metadata.*

The impact of DQ metadata on decision outcome will vary with task complexity and experience of decision-makers. The consensus among decision-makers will change after adding DQ metadata (Fisher et al. 2003). We argue this may happen for two reasons. First, this may be due to the differences in how decision-makers adjust the decision-model by integrating DQ metadata. We address this by providing a guideline on how to integrate DQ metadata. Second, this may be due to the increased task complexity when DQ metadata is added. As increased task complexity may force decision-makers to adopt different heuristics to reduce cognitive load, each decision-maker arrives at a different outcome. Thus we hypothesize that consensus levels will decrease with increasing task complexity. *H2: When DQ metadata* *is added, the change in consensus among decision-makers will be more apparent for complex tasks than for simple tasks.*

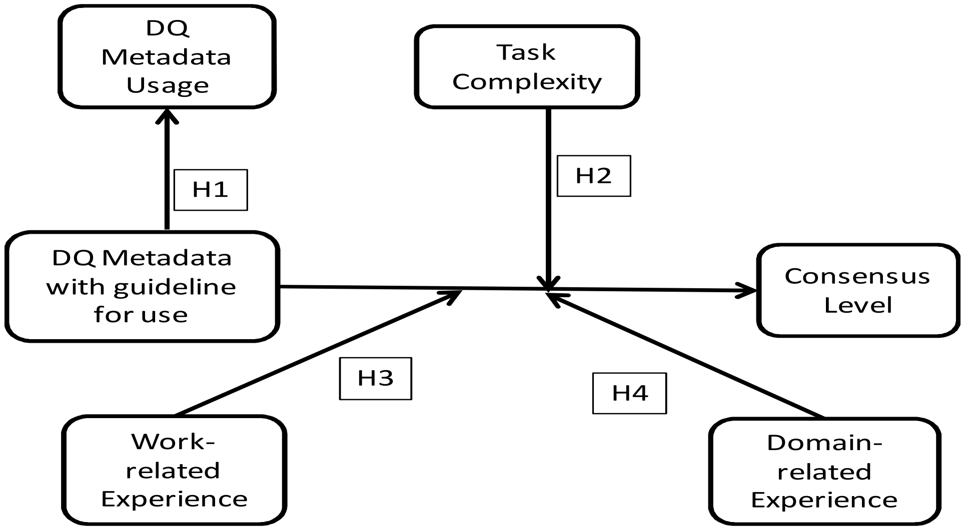

Figure 1: Conceptual Representation of the Model

A simple task may remain simple and not become sufficiently complex after adding DQ metadata. A complex task may however, tax the decision-maker's cognitive capacity. With more work experience, with complex tasks, decision-makers can organize and process data better, and therefore utilize DQ metadata more efficiently. Though we expect consensus to change with DQ metadata, we expect it to be more apparent for decision-makers with less work-experience. *H3: For complex tasks, with DQ metadata, the change in consensus among decision-makers with less work experience is more apparent than among decision-makers with more work experience.*

From our earlier discussion on domain-related experience, we posit that decision-makers with more domain-related experience will utilize DQ metadata better when handling complex tasks. H4: *For complex tasks, with DQ metadata, the change in consensus among decision-makers with less domain-related experience is more apparent than among decision-makers with more domain-related experience.*

Task Design: Similar to prior studies (Fisher et al. 2003), we used structured decision tasks that required the weighted-additive strategy. Two tasks were designed involving the ranking of digital cameras, a domain that most of our subjects were familiar with. We varied the number of decision variables and alternatives to manipulate complexity. The simple task required ranking four digital cameras over five attributes (20-cell decision space) and the complex task required ranking seven cameras over eight attributes (56-cell decision space). Each attribute had a weight associated that indicated the importance of that attribute to the users of digital cameras. Participants were informed that these weights were based on market-research and may not be accurate. There was an accuracy measure (a percentage) associated with each weight, representing the DQ metadata. A method for incorporating the accuracy measure (DQ metadata) into the decision model was provided to all participants.

Experiment: We recruited participants (59 graduate and 76 undergraduate, 59 females and 74 males, 2 did not report gender) from among a subject pool of students in a large university. Participants were randomly assigned to the control or experimental group. Each group performed a simple and a complex decision-task, the order of which was randomly assigned. Although both groups had the same decision model, task data, and basic instructions on how to develop the decision model, the control group did not receive the DQ metadata while the experimental group did, along with the guideline to incorporate the metadata. An online survey was designed to collect demographic data (before the start of the experiment), provide task descriptions and instructions (one task at a time), collect solutions and track the time spent by each participant on each task.

Results and Analyses

The average age of our subjects was 23.07 and average work experience was 2.26 years. We surveyed the number of cameras owned/used as a measure of the domain-related experience, with the average being 1.66. We determined no significant difference in age (t=1.124, p=0.262), work experience (t=0.706, p=0.481), or number of digital cameras owned/used (t=0.525, p=0.60) between the control and experimental groups. We classified subjects with less than 2 years of work experience or with one/no digital cameras as "less-experienced" with respect to work and domain-related experiences. Subjects with more than 2 years of work experience or that own/use more than one camera as "experienced". As a manipulation check, we asked each subject to rate perceived complexity after each task. We reasoned that subjects with DQ metadata are likely to perceive a task as more complex than the subjects without DQ metadata for the same task. We also reasoned that tasks with more alternatives will be seen as more complex. Our analyses confirmed this reasoning: subjects perceived tasks with DQ metadata (N=123; mean=3.098) to be more complex (t=-3.462, p=0.001) than tasks without DQ metadata (N=128, mean=2.288). They also perceived the task with more alternatives (N=129, mean=3.047) to be more complex (t=-3.295, p=0.001) than the task with less alternatives (N=132, mean=2.356).

Table 1: Summary results for Complacency

Summary of Complacency		Less Wk. Exp		More Wk. Exp		Less Dom-Rel Exp		More Dom-Rel Exp	
		N	**Complacency**	N	**Complacency**	N	**Complacency**	N	**Complacency**
Simple Task	Without DQ	36	$\chi2$ =47.91	32	$\chi2$ =67.00	35	$\chi2$ =55.09	33	$\chi2$ =59.12
	With DQ	30	p < 0.00	35	p < 0.00	35	p < 0.00	30	p < 0.00
Complex Task	Without DQ	33	$\chi2$ =20.36	34	$\chi2$ =44.36	32	$\chi2$ =27.59	35	$\chi2$ =35.87
	With DQ	31	p < 0.00	32	p < 0.00	32	p < 0.00	31	p < 0.00

Table 2: Summary results for Consensus

Summary of Consensus		Less Wk. Exp		More Wk. Exp		Less Dom-Rel Exp		More Dom-Rel Exp	
		N	**Consensus**	N	**Consensus**	N	**Consensus**	N	**Consensus**
Simple Task	Without DQ	36	$\chi2$ =0.391	32	$\chi2$ =0.928	35	$\chi2$ =1.061	33	$\chi2$ =0.458
	With DQ	30	p = 0.532	35	p = 0.335	35	p = 0.303	30	p = 0.498
Complex Task	Without DQ	33	$\chi2$ =4.407	34	$\chi2$ = 0.209	32	$\chi2$ =4.947	35	$\chi2$ =0.066
	With DQ	31	p <= 0.044	32	p = 0.648	32	p = 0.026	31	p = 0.798

As discussed earlier, we measured the use of DQ metadata using complacency and consistency measures. Similar to Chengalur-Smith et al. (1999) we measured complacency by first counting the number of subjects without DQ metadata who chose the optimal alternative as their top choice. We then counted the number of subjects with DQ metadata who chose the same optimal alternative as their top choice. We ran a Chi-square test of homogeneity to measure complacency – a significant chi-square value indicates a lack of complacency. The consistency measure is required only if the two sets of decision outcomes have the same complacency score. In our study, the top choices changed significantly, obviating the need for measuring consistency.

We also measured the impact of DQ metadata using consensus. In our study, the decision outcome is the list of decision alternatives (the cameras) in order of preference (top choice first). The frequency of the most preferred choices from the two groups (with and without DQ metadata) were captured. Differences in frequencies of the most preferred choices between the two groups were tested using Chi-square. A significant chi-square statistic indicates a significant change in consensus. The ideal situation would be to have a significant chi-square statistic for complacency and an insignificant one for consensus – indicating the strong use of DQ metadata and its use in a consistent way with near identical results.

Hypothesis H1 theorized that decision-makers, regardless of experience, will use DQ metadata if guided on how to integrate it. Significant chi-square values (shown in table 1) for complacency indicate that decision-makers with more and less work experience changed their top choices after integrating DQ metadata. A similar behavior was observed with manipulating domain-related experience. *H1 was supported* (all p values were significantly lower than 0.05).

Hypotheses H2 theorized that the impact of DQ metadata on consensus among decision-makers will be more apparent for the complex task than for a simple task. *H2 was supported for decision-makers with less work experience and not supported for decision-makers with more work experience*. As seen in table 2 (under Less Wk. Exp.), the chi-square values were insignificant for the simple task and significant for the complex task, indicating that consensus among decision-makers with less work experience did not change after the integration of DQ metadata into the simple task, but, changed significantly after DQ metadata was integrated into the complex task. We tested this further by assigning each subject a consensus score of 1 if his/her top choice was the same as the popular top choice for the group and, 0, if it was not. For the simple task, an independent T-test revealed that there was no significant difference (t=-0.618, p=0.539) in the consensus score among decision-makers with less work experience, between the control group (N=36, average-score=0.889) and the experimental group (N=33, average-score=0.933). For a complex task, the control group (N=33, average-score =0.758) had significantly higher (t=2.036, p=0.046) consensus score than the experimental group (N=31, average-score = 0.516).

Similar results were seen for the decision-makers with less domain-related experience. The chi-square statistic for consensus was insignificant for the simple task and significant for the complex task. Upon further testing using the consensus score (described above), the independent T-test appeared to indicate no significant difference (t=-1.023, p=0.311), in the case of a simple task, in the consensus scores of decision-makers with less domain-related experience between the control group without DQ metadata (N=35, average-score=0.914) and the experimental group (N=35, average-score= 0.971). However, with the complex task, the experimental group (N=32, average-score=0.594) had a lower consensus score (t=2.279, p=0.026) than the control group (N=32, average-score=0.844). H2 was not supported for decision makers with more work or domain-related experience. For decision-makers with more work experience, comparing the control and the experimental group we found non-significant chi-square statistic for both simple and complex tasks (see column 2, More Wk. Exp. in table 2). The results were similar with domain-related experience (see column 4, More Dom-Rel-Exp. in table 2).

Hypothesis H3 theorized that for a complex task, the inclusion of DQ metadata will have a more apparent impact on consensus level among decision-makers with less work experience than on the same consensus among decision-makers with more work experience. *H3 was supported*. For a complex task, for decision-makers with less work experience, the chi-square statistic was significant ($\chi 2=4.047$, p=0.044) when comparing the groups with and without DQ metadata. For the same complex task, for decision-makers with more work experience, the chi-square was non-significant ($\chi 2=0.209$, p=0.648). This indicates that there was a shift in consensus when DQ metadata was included for decision-makers with less work experience and the same shift was not significant for decision-makers with more work experience. This was further tested using the consensus score – an independent T-test revealed that decision-makers with less work experience had a much more diversified set of decision outcomes (t=2.036, p=0.046) when comparing consensus scores across the groups with and without metadata. A similar test also indicated that the consensus scores were similar (t=0.450, p=0.654) for decision-makers with more work experience, when comparing the two groups (with and without DQ metadata) indicating that the decision outcomes were similar for the two groups.

Hypothesis H4 theorized that for a complex task, DQ metadata will have a more apparent impact on consensus level among decision-makers with less domain-related experience than on the consensus among decision-makers with more domain-related experience. *H4 was supported*. The significant chi-square statistic for decision-makers with less domain-related experience ($\chi 2= 4.947$, p= 0.026) indicates that using DQ metadata significantly changed the consensus. We obtained a non-significant chi-square statistic ($\chi 2=0.066$, p=0.798) for decision-makers with more domain-related experience for the complex task, suggesting that the inclusion of DQ metadata did not cause a significant change in consensus. The result from the T-test, using the consensus score, revealed that decision-makers with less domain-related experience had significantly lower consensus (t=2.279, p=0.026) in the group using DQ metadata than in the group without DQ metadata. But, considering decision-makers with more domain-related experience, there was no statistically-significant difference in the consensus score ($t=0.252$, $p=0.802$,) between the groups with and without DQ metadata.

Discussion

The results indicate that decision-makers will use the DQ metadata when they know how to use it, regardless of task complexity and decision-maker's experience. It appears that some decision-makers were overloaded by the extra data due to DQ metadata. Consequently, the consensus among decision decision-makers with DQ metadata decreased.

Effects of Task Complexity: While providing guidance encourages the use of DQ metadata, it sparks a decrease in consensus among decision-makers, depending on the complexity of the decision-task. For a simple task, adding DQ metadata does not increase task complexity to the extent of overwhelming a decision-maker. Therefore, the consensus within a group remains the same, before and after the inclusion of DQ metadata. On the other hand, incorporating DQ metadata into a complex decision-task makes it too complex. Decision-makers, instead of trying, resort to reducing complexity using heuristics, when they perceive the task to be too complex (Streufert, 1973). Consequently, decision-makers who were overloaded reached different decision outcomes than those who were not. The consensus thus decreases. Hypothesis *H2* theorized that the impact of DQ metadata on the consensus is more apparent for a complex task than for a simple task. Our results indicate that this was supported only for decision-makers with less work experience or with less domain-related experience.

H2 was not supported for decision-makers with more work experience. A reason could be that decision-makers with more work experience can process more task-related data than those with less work experience (Mao and Benbasat, 2000). Although DQ metadata increased complexity, those with more work experience were not overwhelmed. They were able to maintain similar consensus levels among themselves before and after the inclusion of DQ metadata. While the inclusion of DQ metadata in a complex task increased the task complexity beyond the cognitive limit of less experienced people, those with more work experience found it manageable.

A similar explanation can be offered as to why H2 was not supported for decision-makers with more domain-related experience. People have more domain-related experience have a strong interest in tasks in their domain (Schiefele et al., 1992). They are less likely to give up, even as task complexity increases, as performing an interesting task stimulates pleasant emotions that encourage people to work harder (Schiefele, 1992; Tobias, 1994). Therefore, when adding metadata to an already complex task, decision-makers with more domain-related experience were able to accomplish the task effectively. Even after the inclusion of DQ metadata, decision-makers with more domain-related experience were able to maintain similar consensus among themselves, just as their counterparts without DQ metadata did.

Effects of Work Experience: H3 examined the mediation effect of work experience. The conclusions from the testing H2 were further validated by analyzing the results for *H3*. People with more work experience can effectively process more task-related data. Therefore a task that appears to be complex to decision-makers with less work experience could appear simple to those with more work experience. The complex task may appear even more complex with the inclusion of the DQ metadata to less experienced participants who resort to guesses and heuristics. However, the same task appeared less complex to experienced participants and they did locate the optimal solution. Consequently, using DQ metadata significantly decreased consensus level among people with less work experience and did not significantly affect the consensus level among those with more work experience.

Effects of Domain Specific Experience: *H4* examined the mediation effect of domain-related experience. More domain-related experience motivates people to finish complex tasks. It is possible that a complex task appears to be complex to both more experienced and less experienced decision-makers. But it takes higher task complexity for those with more domain-related experience to give up than it does for those with less domain-related experience. Consequently, while DQ metadata increased complexity of a complex task, it significantly decreased the consensus level only among decision-makers with less domain-related experience.

The above findings have important implications for decision support. First, organizations wishing to provide DQ metadata should not rely on individual decision-maker to decide if and how to use the DQ metadata. Instead, they need to provide guidelines on how the data should be used. This is consistent with Fisher et al. (2003) that suggested organizations to provide educational seminars on DQ metadata before providing it. Second, managers should be aware that although providing a guideline can help decision-makers agree with each other after using DQ metadata, it cannot guarantee an optimal decision outcome. Thus organizations should consult with decision-makers to come up with an appropriate guideline. How to develop such guidelines could be another stream of research. Third, when including DQ metadata, providing guidelines on how to use DQ metadata does not eliminate all the causes for the decrease in consensus among decision makers. Managers should be aware that the positive impact of the DQ metadata on decision-tasks depends on the nature of the decision-task and the characteristics of the users. Either additional support for the task should be provided, or more experienced users may be assigned to it. A challenge with this complexity-based approach is that decision-makers with more work experience and those with less work experience are likely to have different criteria for what constitutes a complex task. In addition, decision-makers with differing domain-related experiences give up on a task at differing complexity levels. Therefore one avenue for research to clarify this model is investigating the operationalization of complexity in the context of variations in task and types of experiences. Finally, research in information visualization has shown that the applying visualization techniques can reduce the mental effort of understanding data (Card et al., 1999). Therefore, using visualization to reduce the overload caused by the inclusion of DQ metadata is a promising direction for future research. The model proposed provides a framework for evaluating the design (including visualization and design of the front-end interfaces) efforts to help improve the effectiveness of DQ metadata.

Conclusion

In this paper, we demonstrated that decision-makers will use DQ metadata when guidance on how to use it is provided, independent of the complexity of the task and the experience of the decision-maker. Further, this paper uncovered the situations when DQ metadata has a negative impact on consensus levels, even when guidance on how to use DQ metadata is offered. We identified the circumstances under which DQ metadata offers a positive impact on decision outcome. We did so by first developing a robust model founded on good theoretical footing. We then derived a set of hypotheses from the model and using a controlled experimental setting, validated our hypotheses. Our findings support our theoretical claims. Generalization of the model and associated results are limited by the domain of structured decisions and the specific method for integrating DQ metadata into the decision process. It is also limited by the fact that it uses student participants. Despite this, we believe that these results are of widespread interest to researchers and practitioners. In addition, as the provision and use of DQ metadata becomes increasingly ubiquitous in the design of decision environments, we need guidelines to understand and to assess why DQ metadata supports different decision-tasks differently. The model proposed is theoretically robust and parsimonious enough to inspire others to refine it.

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