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A Quasi-Experimental Analysis on the Influence of Satisfaction and Complexity on Information Quality Outcomes

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Abstract

It has been reported that more than two thirds of users are satisfied with the quality of the data they process at work. However, literature suggests that IQ (information quality) problems are becoming progressively prevailing. We perform a quasi-experimental analysis and investigate both, main effects of satisfaction and complexity as well as interaction effects of them. For information quality outcome we use users' perception of the importance of IQ dimensions. We find evidence for main effects of both factors as well as an interaction effect on various dimensions of IQ. Satisfaction levels influence the perceived importance of conciseness and security; Complexity levels influence the perception of conciseness; and accuracy and timeliness are found to be influenced by interactional effects. We discuss potential implications of the findings and suggest more experimental research in this domain.

Key Words

Information quality, complexity, user satisfaction, experimental methodology, organizational impact

1. Introduction

It has been reported that more than two thirds of users are satisfied with the quality of the data they process at work (Fehrenbacher and Helfert 2012). However, the literature suggests that information quality (IQ) problems are becoming progressively prevailing (Lee et al. 2002). According to Fisher et al. (2006) IQ problems cost U.S. businesses more than 600 billion dollars a year. One problem is that companies have far more data than they possibly use, but may not have the data they actually need (Abbott 2001). In 2012 the amount of digital data increased to 2.8 zettabytes (EMC 2012). Despite the increasing sophistication of search and analysis tools, the mere quantity of data contributes to data complexity and may affect IQ outcomes.

Thus, important questions that remain unanswered are whether satisfaction and complexity levels can be linked to IQ outcomes. Answering these question will contribute to the better understanding of influencing factors on IQ outcomes which may in turn influence individual performance and organizational impacts (DeLone and McLean 1992). This quasi-experimental analysis is related to the study of Fehrenbacher and Helfert (2012) who show that available resources, information and communication technology as well as the decision environment influence users' views on IQ. We address two neglected influence factors in more depth. We propose that data and information users' satisfaction as well as the complexity of the data at hand influences users' views on IQ. We perform a quasi-experimental analysis and investigate both, main effects of satisfaction and complexity as well as interaction effects of them. As information quality measure we use users' perception of the importance of IQ dimensions.

The paper is structured as follows. First, a brief overview of related satisfaction, complexity and IQ literature is presented thereby developing the propositions. Subsequently, we discuss the methodology and particularly focus on experimental and quasi-experimental requirements for studying IQ. Then, we present the results and discuss implications, limitations and conclude the work.

2. Literature Overview and Proposition Development

2.1 Satisfaction Research

User satisfaction is foremost a subjective concept influenced by individual characteristics and the user environment, such as task demands (Goodhue 1995). It is often regarded as the most useful and easiest way to evaluate an information system (IS, Islam 2011).[1] User satisfaction has received considerable attention in the IS literature since the 1980s. Bailey and Pearson (1983) model user satisfaction and develop a measure involving 39 components elicited by the use of four pairs of confronting adjectives per component. Doll and Torkzadeh (1988) discuss the measurement of user satisfaction and propose four components of user satisfaction: content, accuracy, format, ease of use, and timeliness. These components, their measurement and their relation to user satisfaction have been widely used and discussed (Chin and Newsted 1995). Most prevalent are questions of factors influencing satisfaction. For instance, Baroudi et al. (1986) ask whether user involvement in the development of ISs increases user satisfaction. They are able to evidence relationships. Huang and Davison (2011) evidence influences of price, product quality and service quality on economic satisfaction or service quality on social satisfaction in a C2C online shopping context. Satisfaction then supports online loyalty. Islam (2011) additionally asks for factors influencing dissatisfaction.

Interestingly, many components of user satisfaction resemble the dimensions of IQ (Fehrenbacher and Helfert 2008, Blake 2010). Most commonly IQ is conceptualized subjectively and is thought of as information that is 'fit for use' (Ballou et al. 2003). This implies that quality of data is seen as relative, because data considered appropriate for one use may not possess sufficient quality for another use. Thus, there is reason to believe that there are relations between user satisfaction and IQ dimensions when perceived subjectively. However, to our best of knowledge direct relations between IQ and user satisfaction have not been tested.

Additionally, the question of causality is raised. Most studies investigate factors influencing satisfaction (Zviran and Erlich 2002, Briggs et al. 2008). In this study we model satisfaction as independent variable, thus we investigate whether satisfaction levels have an influence on IQ outcome or IQ demands through importance perceptions.

In **Proposition 1** we suggest that user satisfaction influences IQ perception.

[1] Reviews can be found in Zviran and Erlich (2002) or Islam (2011).

2.2 Complexity Research

Since the 1980s task complexity has received considerable attention. Wood (1986) divides task complexity into three dimensions: component complexity, coordinative complexity and dynamic complexity. Task complexity may increase information processing demands and requires more cognitive resources from the individual. The most prevalent and acknowledged approach in the study of task complexity has been to elicit individuals' perceptions of task complexity (Wood 1986).

In economics and psychology complexity is linked to attention span. Since people's attention capacity is limited, consistent attention for an unlimited period cannot be assumed. Attention may be affected as individuals get bored with the task or as individuals get overtaxed by the task's demand (Kahnemann 2011 p.39ff.). With low complexity the former rational is more likely, with high complexity of the task at hand the latter rational is more likely. Prior IS research shows that complexity has an influence on users' and consumers' cognitive processes and outcomes. Cui et al. (2012) develop a measure of perceived website complexity and relate it to cognitive style. They find that people with holistic and analytic cultural cognitive styles display different perceptions of website complexity. Jung et al. (2005) investigate differences in problem solving accuracy for two IQ variables (contextual data quality and task complexity) and investigate their influence on decision performance (accuracy of problem solving and solution time). They find an influence of contextual data quality but do not evidence differences in decision performance between low and high levels of complexity.

Payne (1976) shows that information processing leading to choice varies as a function of task complexity. When decision tasks get more complex, individuals tend to use simplifying heuristics (Payne et al. 1993 p.34ff. for an overview). That may lead to the assumption that in order to facilitate information processing, users have different demands for the quality of data depending on task complexity. In an IQ context it may be desirable to know whether individuals prefer certain IQ characteristics in complex vs. simple data or decision tasks. In terms of online consumers', it has been shown that complexity influences presentation format effectiveness for delivering product knowledge: In a low task complexity setting static pictures are less effective than videos whereas in a high task complexity setting static pictures are equally effective as videos (Jiang and Benbasat 2007). In a similar vein Speier and Morris (2003) find that under low task complexity decision makers' performance is more accurate when using text-based interfaces, whereas under high task complexity decision makers' accuracy is better when using visual interfaces.

One rational may be that in order to simplify complex data the presentation format of the data may be of more importance to the decision maker than in a simple data environment. When users choose simplifying heuristics for complex tasks (Payne et al 1993 p.34ff.), they may consciously perceive conciseness of the information as more important than security of information. It may also be that in complex tasks users have higher demands for consistently represented information, in order to facilitate the information processing. On another account, timely information maybe more important with complex data at hand in order to not having to process information twice: once with out-of-date information and a second time with up-to-date information. In line with Goodhue's (1995) study suggesting that system, task and individual characteristics directly influence a user's evaluation of ISs, we suggest in **Proposition 2** that complexity level influences IQ perception.

Additionally, we propose (**Proposition 3**) that user satisfaction and complexity levels have an interaction effect. As interaction effects have not been investigated in IQ research, potential effects are hard to predict. It may be that within complex data settings, satisfaction levels have not as much of an influence on IQ perception as in simple data settings.

3. Methodology

3.1 Limited Approaches in IQ and Suggestion of Experimental Research

The research of information quality is limited in its approaches. A meta-analysis of Lima et al. (2006) shows that survey research only accounts for 9 per cent of the total IQ research and experimental research seems to be non-existent (0 per cent). Conceptual and illustrative research, as classified by Alavi and Carlson (1992), account for the biggest junk in IQ research and holds a share of 54 per cent. Simulations mostly dealing with technological aspects of databases or internet applications as well as with the implementation of software account for 20 per cent of IQ research. Qualitative methodology using case study, participative observation or action research account for 17 per cent. Lima et al.'s (2006) review is not necessarily representative as it mainly sources its articles from conferences; however, the sample of 171 articles is relatively big. In the 2003 special section on Assuring Information Quality in the Journal of Management Information Systems (Ballou et al. 2003) one out of four research studies use a survey approach (Lee and Strong 2003). The others are of conceptual (Cappiello et al. 2003), applied conceptional (Lee 2003) and simulational (Madnick et al. 2003) type.

There is one notable exception when it comes to the application of the experimental method in IQ. Jung et al. (2005) perform an experiment incorporating two treatment variables: contextual data quality and task complexity. They investigate their influence on decision performance. They find an influence of contextual data quality but do not evidence differences in decision performance between low and high levels of complexity. Jung et al. (2005) is an innovative methodological approach in the study of IQ, but does only cover limited aspects of IQ.

This research empirically examines the influence of satisfaction and complexity using a quasi-experimental design. We try to cover a broad array of IQ outcomes in measuring eight dimensions of IQ. In the subsequent sections we give a brief overview of basic experimental elements, introduce our quasi-experimental IQ design as well as the measures used.

3.2 Quasi-Experimental Approach for IQ Research and Underlying Measures

Cook and Campbell (1979), p. 5 state requirements, which an experiment should have: a *treatment*, *assignment units*, *outcome measure* and an *instrument* by which relationships between the treatments and the *outcome measure* can be inferred and attributed to the treatment. Sarris (1992), p. 129 adds that an experimental investigation needs to pay particular attention to controlling potential systematic or unsystematic *confounding factors*. All requirements should be considered in IQ research and this quasi-experimental methodology. They are briefly discussed in the following.

A design involving participant variables as independent variables can be called a quasi-experimental-design (Evans and Rooney (2008), pp. 194f.). In a quasi-experimental design a researcher lacks the full control over the *treatment*, because the participants not the researcher assign themselves to different levels of the variables (Cook and Campbell 1979). Still, as the different levels can be interpreted as different treatments, the data can be analysed following experimental designs.

In the underlying design we use the participant ratings of satisfaction as well as complexity to assign subjects (*assignment units*) to an experimental treatment group. Satisfaction is prompted by the question "Are you satisfied with your data quality at work in general?" with a binary response choice 'yes' or 'no'. For this binary response option, the data can be coded in a dichotomous variable and can be used directly to assign subjects to two conditions. A condition in which participants perceive 'high' satisfaction and a condition involving 'low' satisfaction.

Complexity is prompted by the question: "Rate the complexity of your activities for collecting, storing & using the information on average." and measured on a scale from 1 = 'Very simple' to 9 = 'Very Complex'. In this case, as discussed above economic reasons limit the sampling and assignment process. Considering sample size nine levels in this variable are too many. In this case, dichotomization can be used to decrease a variable's level of measurement. In order to decrease levels of a variable and facilitate the analysis of quasi-experimental designs, dichotomization is a common practice in empirical research (Ravichandran and Fitzmaurice 2008, p. 610). Such an analysis might pave the way for illustratively presenting findings and could provide a good fit with modelling because many models also distinguishes between high and low values of attributes exemplarily. In order to achieve such a dichotomization, median splits are the most frequent method (Irwin and McClelland 2003).[2] The complexity levels median is 5. We use a median split in excluding the median. Thus, we rather look at more extreme levels of complexity by including the values 6-9 for the 'high' complexity condition and including the values 1-4 for the 'low' complexity condition. In addition to the main effects, interaction effects of satisfaction and complexity are expected. Figure 1 shows the experimental design.

As information quality *outcome measures*, i.e. dependent variables, we use participants' ratings in which participants have to trade-off IQ dimensions in a ranking of importance. This method has proven superior in terms of better distinguishing the priorities of users (Fehrenbacher and Helfert 2012). In this question type participants have to consider resource limitations as they are not able to denote all dimensions with high importance. The dimensions are selected through a literature review focusing on IQ dimensions which have potential trade-offs. IQ studies often mention the importance of trade-offs (Ballou and Pazer 1995). In order to denote the relative importance of the IQ dimensions a total of 40 points could be allocated to eight criteria (method of constant sum and comparative scaling). The primary advantage of this constant sum scale is that it allows for fine discrimination among stimulus objects without requiring too much time. The eight dimensions considered are: Accessible, Accurate, Believable, Complete, Concise, Consistently Represented, Secure and Timely.

[2] However, there are problems associated with dichotomizing quantitative predictor variables. Loss of statistical power (e.g. in case of predictor's normal distribution), decreased validity of the statistical analysis (e.g. in case of U-shaped relationships) or subjectivity of cut-point choice and thus loss or generalizability of the results are problems stated in methodological literature. Hence, caution is warranted whenever such classification of quantitative data leads to a loss of information. In general, the fewer steps there are in a multistep variable, which is derived from a rating scale, the less is the loss of statistical power due to dichotomization (Ravichandran and Fitzmaurice 2008).

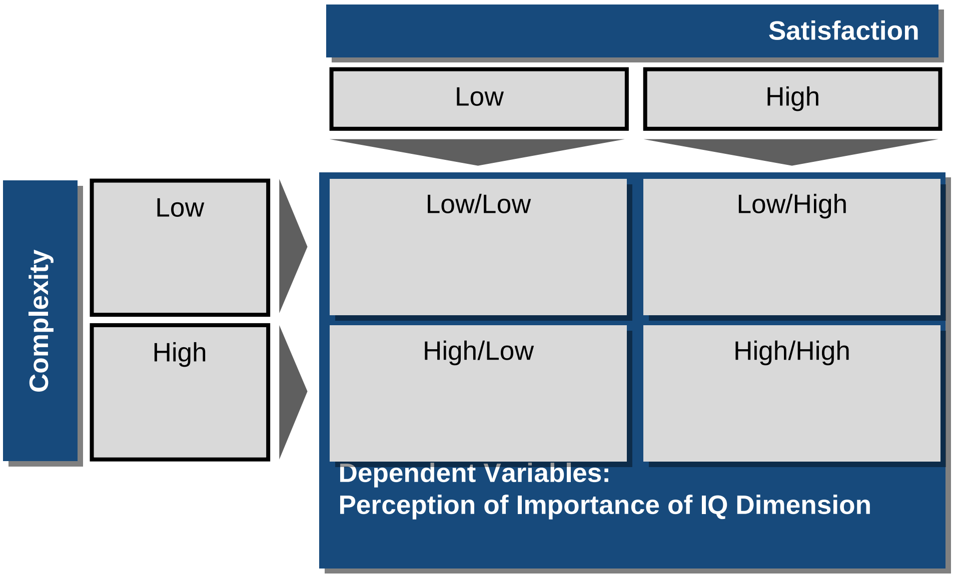

Figure 1: Quasi-experimental design

As *instrument* for inferring relationships we use the general linear regression model presented in an ANOVA paradigm:

IQ outcome = *f* (intercept, satisfaction, complexity, satisfaction x complexity)

Since this study is ‘only’ a quasi-experiment, the possibility to control for potential systematic or unsystematic *confounding factors* is limited. The decision context of the individuals responding to the questionnaire is different. However, patterns found may be still generalized as perception differences might have similar effects across contexts.

3.3 Data Collection

The data was collected by a pre-tested questionnaire, which was pre-discussed with both academics and practitioners. 2,558 people received information about the survey via different means spanning a wide spectrum of professionals and students with professional experience. 1,952 students of both the Dublin City University Business School (Ireland) and the European School of Business (Reutlingen, Germany) were addressed. Since the targeted students have to complete mandatory internships (minimum six months duration), a large percentage of students had professional experience in the business domain, particularly since final year students were primarily addressed. However, it cannot be excluded that less-experienced students completed the questionnaire. In addition, the survey was spread through a newsletter of the International Association of Information and Data Quality addressing 364 members. Furthermore, 242 people associated with the “Deutsche Gesellschaft für Informations—und Datenqualität” were addressed through an online community. The questionnaire was preceded by a cover letter (e-mail, web-posting) explaining the nature of the study and its criticality. 234 people responded to the survey, i.e. an estimated response rate of 9.12 per cent. The number of respondents decreases towards the end of the survey because of quitters. We use questions 1 (satisfaction), 6 (complexity) and 10 (IQ output) for the quasi-experimental analysis.

4. Results

Proposition 1 expects satisfaction level to have an influence on IQ outcome. Table 1 shows individual ratings of IQ dimension importance for participants with ‘high’ as well as ‘low’ satisfaction levels. Interestingly, 5 out of 8 IQ dimension means decrease with ‘high’ levels of user satisfaction. When comparing the row ‘rank’ for participants with ‘high’ as compared to ‘low’ satisfaction levels the same pattern can be observed for accuracy, accessibility and completeness. These three dimensions are the three most important characteristics and are ranked in the same order by satisfied users as well as dissatisfied users. The IQ dimension security differs most widely in terms of ranking. The satisfied users rank it as the fourth most important criteria, whereas the unsatisfied users rank it as the least important criteria. Statistical significance is confirmed at the 0.05 level by an analysis of variance ($F = 5.487$, $p = 0.021$). In addition, conciseness is significant at a 0.1 level ($F = 2.957$, $p = 0.088$). It is rated more important by satisfied users as compared to unsatisfied users (Table 1). The other dimensions are not found to be statistically different.

One interpretation may be that satisfied users place more weight on qualitative aspects of IQ as security or conciseness than on quantitative aspects as accuracy, accessibility or completeness which can be more easily quantified or verified. The less weight satisfied users place on accuracy or accessibility cannot be proven in a statistically significant sense, but descriptively this difference is notable and becomes particularly obvious in Figure 2. 5 out of 8 IQ dimension means decrease with ‘high’ levels of user satisfaction, whereas three IQ dimension means increase in importance rating. Thus, satisfied users seem to have particular points of interest.

Table 1: Perception of Importance of IQ Dimension per Satisfaction Level (High/Low)

Satisfaction		Accessible	Accurate	Believable	Complete	Concise	Consistently Represented	Secure	Timely
High	Mean	6.93	7.34	4.31	5.56	3.56*	3.30	4.74**	4.26
	Rank	2	1	5	3	7	8	4	6
	N	70	70	70	70	70	70	70	70
	Std. Deviation	5.420	3.413	3.151	2.652	2.288	2.081	3.193	3.229
Low	Mean	7.16	7.86	4.92	6.14	2.88*	3.53	3.45**	4.06
	Rank	2	1	4	3	8	7	8	5
	N	51	51	51	51	51	51	51	51
	Std. Deviation	4.818	3.213	2.965	3.244	1.894	2.556	2.700	2.671
Total	Mean	7.02	7.56	4.57	5.80	3.27	3.40	4.20	4.17
	N	121	121	121	121	121	121	121	121
	Std. Deviation	5.155	3.326	3.076	2.917	2.149	2.286	3.051	2.996

Notes: * significant from other treatment group at the 10 per cent level; ** significant from other treatment group at the 5 per cent level; *** significant from other treatment group at the 1 per cent level;

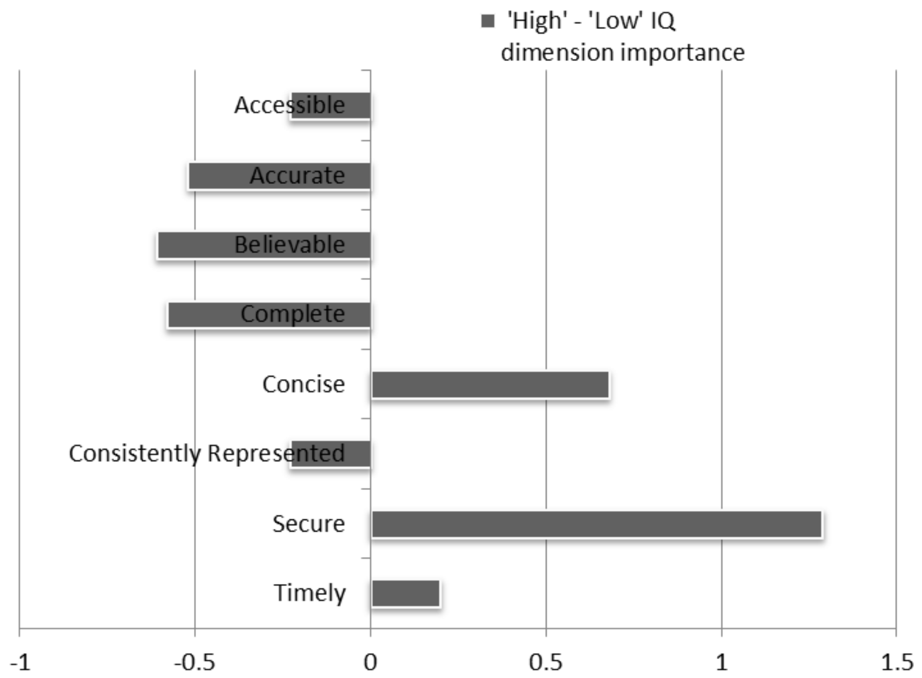

Figure 2: Difference in IQ dimension importance rating of ‘high’ vs. ‘low’ satisfaction group

Proposition 2 expects that the perceived complexity has an influence on IQ outcome. Table 2 shows the importance ratings of the IQ dimensions for ‘high’ as well as ‘low’ complexity levels. The total number of responses is lower than in Table 1. This is because of the median split performed, leading to an exclusion of the ‘middle’ rating 5. Again, considering the row ‘rank’, number one to three are accuracy, accessibility and completeness in both conditions. Two dimensions, being believability and security, have two ranks difference. However, an analysis of variance performed does not result in significant differences for believability ($F = 0.362$, $p = 0.549$) or security ($F = 0.619$, $p = 0.433$). Only one dimension, i.e. conciseness, is significant at the 0.1 level ($F = 3.246$, $p = 0.075$). Interestingly, users who perceive information as complex, rate the importance of conciseness lower than users who perceive information as less complex.

The interpretation at this point is not straightforward. If we get back to Payne (1992) and the simplifying heuristics, one may conclude that information users in complex settings do not necessarily express the importance of making data more concise as compared to other IQ dimensions. Other simplifying heuristics may be more important. Another rational may be that users who perceive their data as complex also acknowledge the fact that the data cannot be expressed in a more concise way because of the data’s complex nature, which is why they do not rate conciseness as being relatively important as compared to users in ‘low’ complexity settings.

Proposition 3 expects interaction effects in a way that different satisfaction levels impact IQ perceptions in a different way for simple as compared to complex data settings. It may be that within complex data settings, satisfaction levels have not as much of an influence on IQ perception as in simple data settings. The results are surprising. We find significant interactions for accuracy as well as timeliness. However, we do not find that the change in satisfaction levels is more distinct for users in simple settings as compared to users in complex settings. Both conditions reveal a change, but the change, to our surprise, is in different directions. Table 3 shows the descriptive results for the accuracy and timeliness ratings per treatment variable, treatment condition as well as overall figures as proposed in the experimental design of Figure 1. We show these two IQ dimensions as they show significant interactions. Let us take the ‘high’ complexity condition: when satisfaction is ‘high’ accuracy importance is rated at 8.78; when satisfaction is ‘low’ accuracy is rated at 7.28 (Table 3). Thus, the rating decreases from ‘high’ to ‘low’ satisfaction levels, i.e. with decreasing satisfaction. Now, let us look at the ‘low’ complexity condition: when satisfaction is ‘high’ accuracy importance is rated at 6.72; when satisfaction is ‘low’ accuracy is rated at 8.00. Thus, the rating is reversed. It increases from ‘high’ to ‘low’ satisfaction levels, i.e. with decreasing satisfaction. The GLM test of between subject effects (Table 4) confirms statistical significance for this interaction effect at the 0.05 level.[3]

Table 2: Perception of Importance of IQ Dimension per Complexity Level (High/Low)

Complexity		Accessible	Accurate	Believable	Complete	Concise	Consistently Represented	Secure	Timely
High	Mean	7.29	7.63	4.46	5.95	2.96*	3.39	3.98	4.34
	Rank	2	1	4	3	8	7	6	5
	N	56	56	56	56	56	56	56	56
	Std. Deviation	6.008	3.222	2.898	2.645	1.935	2.395	3.177	2.849
Low	Mean	6.51	7.86	4.14	5.56	3.74*	3.49	4.47	4.23
	Rank	2	1	6	3	7	8	4	5
	N	43	43	43	43	43	43	43	43
	Std. Deviation	4.020	3.075	2.315	2.612	2.371	1.956	2.823	3.372
Total	Mean	6.95	7.73	4.32	5.78	3.30	3.43	4.19	4.29
	N	99	99	99	99	99	99	99	99
	Std. Deviation	5.228	3.146	2.653	2.625	2.159	2.205	3.023	3.071

Notes: * significant from other treatment group at the 10 per cent level; ** significant from other treatment group at the 5 per cent level; *** significant from other treatment group at the 1 per cent level; The total number of responses is lower than in Table 1. This is because of the median split performed, leading to an exclusion of the ‘middle’ rating 5.

The complexity/satisfaction interaction shows a statistically significant relationship with the IQ dimension timeliness at the 0.05 level as well (Table 3, Table 5). In complex settings, when satisfaction decreases, timeliness gets more important. In less complex data when satisfaction decreases, timeliness gets less important. Figure 3 and Figure 4 plot the estimated marginal means based on the GLM of accuracy and timeliness perceptions per complexity as well as satisfaction condition. The crossing clearly indicates interaction effects.

In sum, in complex settings, when satisfaction decreases, accuracy gets less important, whereas it gets more important in simple settings. In less complex data when satisfaction

[3] The main effects are not significant.

decreases, timeliness gets more important, whereas timeliness gets less important in simple settings.

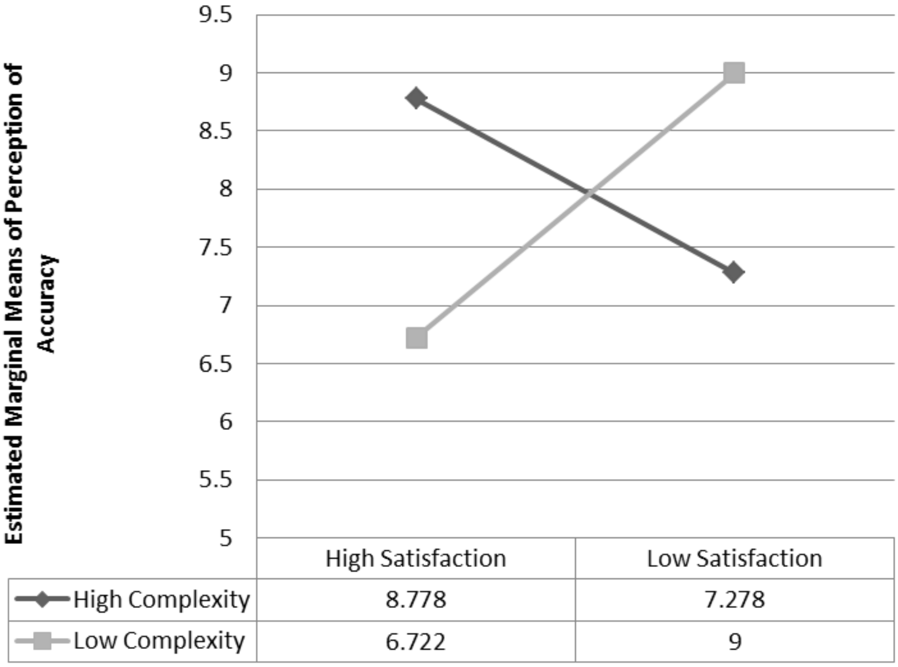

Figure 3: Interaction effects of complexity and satisfaction on accuracy

Table 3: Perception of Importance of Accuracy (A)/Timeliness (T) per Experimental Group - Descriptive Mean (Standard Deviation/Sample Size)

	High Complexity	Low Complexity	Total
High Satisfaction	A: 8.78 (1.48/9)	A: 6.72 (2.35/18)	A: 7.41 (2.29/27)
	T: 3.33 (2.35/9)	T: 5.67 (4.23/18)	T: 4.89 (3.83/27)
Low Satisfaction	A: 7.28 (3.85/18)	A: 8.00 (2.00/9)	A: 7.85 (3.41/27)
	T: 5.22 (2.60/18)	T: 3.78 (2.59/9)	T: 4.76 (2.64/27)
Total	A: 7.78 (3.30/27)	A: 7.48 (2.46/27)	A: 7.63 (2.88/54)
	T: 4.59 (2.64/27)	T: 5.04 (3.82/27)	T: 4.81 (3.26/54)

Notes: In this case an extended median split for the ‘Complexity’ variable is applied, in order to not only exclude the median, but also to exclude ratings of 4 and 6. Thus, we rather look at more extreme levels of satisfaction (‘high’) or dissatisfaction (‘low’).

Table 4: Tests of Between-Subjects Effects: IQ outcome Accuracy

Dependent Variable: **Accurate**

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	45.815[a]	3	15.272	1.934	.136	.104
Intercept	3029.481	1	3029.481	383.695	.000	.885
Satisfaction	1.815	1	1.815	.230	.634	.005
Complexity	.333	1	.333	.042	.838	.001

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Satisfaction * Complexity	42.815	1	42.815	5.423	.024	.098
Error	394.778	50	7.896			
Total	3584.000	54				
Corrected Total	440.593	53				

a. R Squared = .104 (Adjusted R Squared = .050)

Table 5: Tests of Between-Subjects Effects: IQ outcome Timeliness

Dependent Variable: **Timely**

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	45.481[a]	3	15.160	1.467	.235	.081
Intercept	972.000	1	972.000	94.065	.000	.653
Satisfaction	.000	1	.000	.000	1.000	.000
Complexity	2.370	1	2.370	.229	.634	.005
Satisfaction * Complexity	42.815	1	42.815	4.143	.047	.077
Error	516.667	50	10.333			
Total	1814.000	54				
Corrected Total	562.148	53				

a. R Squared = .081 (Adjusted R Squared = .026)

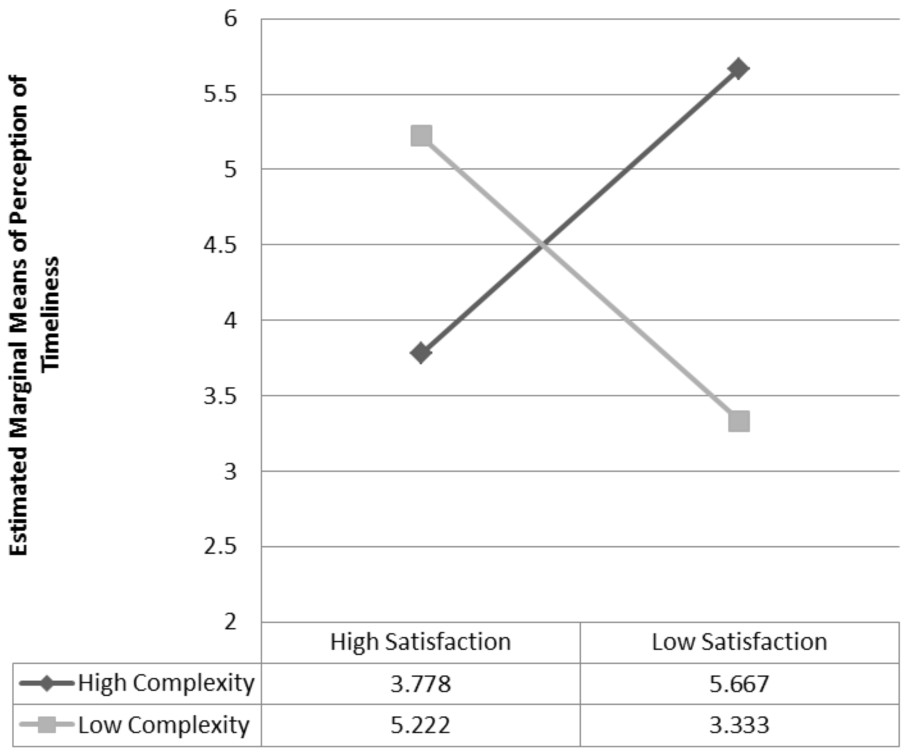

Figure 4: Interaction effects of complexity and satisfaction on timeliness

5. Implications, Limitations and Conclusion

One important finding is that the foremost important dimensions of IQ do not change with complexity or satisfaction: these are accuracy, accessibility and completeness. Independent of satisfaction or complexity conditions these are generally considered to be the most important dimensions forming overall IQ. Thus, IS managers should always consider these dimensions when optimizing IQ. However, several influences of satisfaction and complexity could be still evidenced. It has been found that satisfied users place more weight on qualitative aspects of IQ as security or conciseness than on quantitative aspects as accuracy, accessibility or completeness which can be relatively easily quantified or verified. This maybe a behavioural effect, in a sense that satisfied users take these quantitative dimensions of IQ for granted and, thus, rather stress more qualitative factors. It is also important to note that a variety of IQ dimensions are not found to be in relation with the independent variables. Thus, future research is needed to confirm these findings. Moreover, it has been evidenced that in complex settings, when satisfaction decreases, accuracy gets less important, whereas it gets more important in simple settings. In less complex data when satisfaction decreases, timeliness gets more important, whereas timeliness gets less important in simple settings. We consider this a very notable finding, as there is very little evidence of interactions in IQ research.

Thus, we seek to develop a model incorporating IQ outcome and interactions between satisfaction and complexity in the future. As a foundation DeLone and McLean (1992)'s model of IS success could be used as they address consequences of user satisfaction as well. DeLone and McLean (1992) identify six key factors of IS success. In their model the variable user satisfaction is a central variable influenced by quality characteristics and system use, but also influencing individual performance impact as well as organizational impact. The link between user satisfaction and individual performance impact is particularly interesting for the question at hand. If user satisfaction influences IQ perceptions, the appropriate tuning of IQ dimensions may be done by asking users for their satisfaction. This in turn may enhance individual performance impact and finally organizational performance. Of course, considering the possibility that the tuning of IQ dimensions may affect user satisfaction again, the two components of user satisfaction and importance of IQ dimensions are most likely interdependent.

Admittedly, whether users consciously know what is best for them may be questioned. This is why some studies avoid direct questioning in order to investigate effects (e.g. Jiang and Benbasat 2007). Our data set was gathered using direct questioning for inferring relationships. However, the data was gathered in letting users rate on their importance perceptions by having their specific real decision context in mind. Thus, they for example rate their perceptions having their perceived complex decision environment in mind. However, patterns found may be still generalized as perception differences might have similar effects across contexts. In addition, since hypothetical constructs have been used and have been weaved into the experimental situation, the results are dependent on the strength of these constructs. Distorting factors may be self-serving bias, inattention or strategic motives. The selection and operationalization of the hypothetical constructs have been performed with greatest care. The question for causality can be particularly raised. This study has modelled the effects of satisfaction and complexity on IQ outcome. However, other chain of thoughts might be conceivable as well. IQ outcomes may influence perceived complexity as well as satisfaction. Additionally, other characteristics of the work environment such as the extent of cooperation with team members may have influences on IQ outcome. Moreover, a user might be affected by several company attributes. It might be interesting to observe whether employees of bigger companies tend to have different IQ perceptions than IQ users of smaller companies.

This analysis reverses the causal perspective most studies have had with respect to satisfaction. Most studies asked: what influences user satisfaction (Khalifa and Liu 2002, Islam 2011)? This analysis asks: what effect does user satisfaction as well as complexity have? We show the importance of satisfaction and complexity on users' IQ perceptions and contribute to the better understanding of influencing factors on IQ outcomes. This is particularly important as IQ outcomes influence individual performance and organizational impacts. We call for more experimental research in the field of IQ in order to disentangle effects on and from IQ quality which is an important factor of IS success.

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