Marghescu, D., Rajanen, M., Back, B. (2004). *Evaluating the Quality of Use of Visual Data-Mining Tools*. In proceedings of 11th European Conference on Information Technology Evaluation (ECITE 2004), Amsterdam, Netherlands.

Evaluating the Quality of Use of Visual Data-Mining Tools

Dorina Marghescu
Turku Centre for Computer Science
Åbo Akademi University
Lemminkäisenkatu 14 A, 5th floor
FIN-20520 Turku
Phone: +358-2-2153354
Fax: +358-2-2154809
E-mail: dorina.marghescu@abo.fi

Mikko Rajanen
Department of Information Processing Science
University of Oulu
PO Box 3000
FIN-90014 Oulu
Phone: +358-8-5531926
E-mail: mikko.rajanen@oulu.fi

Barbro Back
Turku Centre for Computer Science
Åbo Akademi University
Lemminkäisenkatu 14 A, 5th floor
FIN-20520 Turku
Phone: +358-2-2154750
Fax: +358-2-2154809
E-mail: barbro.back@abo.fi

Abstract: In this paper we propose a framework for evaluating quality of use of visual data-mining tools. The evaluation framework addresses three levels of analysis: visualization, interaction, and information. We examine the applicability of the framework to the Self-Organizing Maps tools. For this purpose we conducted an exploratory study using the mixed methods research design, and its results are reported in this paper. The conclusion is that our framework can be used for evaluating different visualizations techniques, with small variations from case to case.
Keywords: visual data-mining, usability evaluation, quality of use, Self-Organizing Maps, visualization.

1. Introduction

Data mining is the process of extracting information from large quantities of data by employing advanced computational techniques. Because the data in organizations' databases are rapidly growing, the data-mining activity is not always easy and successful. Users of data-mining tools need fast access to data, real-time interaction with the system, and high-quality information. Whereas traditional algorithmic techniques are analysing the data automatically, information visualization techniques in data mining involve the human to use his/her capabilities to detect structures and to process patterns in data.

The information visualization literature reveals a variety of novel and sophisticated visualization techniques. The problem is that they are not always implemented and/or used to fulfil the real demand of users. One example of such technique is the Self-Organizing Maps (SOM) (Kohonen 2001). The SOM method is a special type of neural network that allows the mapping of high-dimensional data onto a smaller dimensional space, making accessible large amounts of data through a visual model. The capabilities of the SOM technique have been extensively explored in different research areas for more than two decades (Kaski et al. 1998, Oja et al. 2003). Although a large body of research explores the applicability of the SOM method to economic and financial data (Kaski and Kohonen 1996, Back et al. 2000), there is no evidence that business-oriented practitioners use this technique in their work.

This lack of evidence has encouraged us to evaluate the quality of use of the SOM tools. Our approach to evaluating the SOM software consists of three steps: developing a framework of evaluation, selecting the appropriate attributes to measure, identifying the problems and limitations of the SOM tools.

The research problem we intend to tackle in this article is to develop a framework for evaluating the visual data-mining tools from the user perspective (step 1), and to apply it to evaluating the SOM tools (steps 2 and 3). The need of a framework rose because we did not find a suitable model in the literature we reviewed, despite the fact that in the visualization literature, many authors emphasized the necessity for systematic empirical evaluation of visualization techniques (Card et al. 1999, Chen and Czerwinski 2000). The framework for evaluating the quality of use of visual data-mining tools that we propose in this study attempts to clarify the following issues:

- How is the quality of use defined?
- What attributes of the visual data-mining system must be assessed?
- How do these attributes relate?
- How could these attributes be assessed?

Based on established theories and empirical studies reported in the literature, we developed the framework for evaluating the quality of use of visual data-mining tools by taking into consideration three levels of analysis: visualization, interaction and information. For each of the three levels, we identified and described the corresponding attributes.

To examine the applicability of the framework, we conducted an exploratory study on the SOM tools use, and we report the results in this article. The purpose of the study was to examine the attitude of the SOM tools' users, and to shed light on the quality of solutions the SOM users reported. In the quantitative part of the study, we employed the survey technique to collect data about users' attitudes and opinions regarding the SOM tools. The research questions in this part of the study were:

- Determine what attitude the users have regarding the SOM technique,
- Determine the significant relationships between the attributes evaluated,
- Determine the consistency of the measurement.

In the qualitative part of the research, we analysed multiple case studies, collected in the form of reports on the solutions provided by the users to the task given. The research questions for the qualitative part of the study were:

- Determine the quality of the solutions reported by users,
- Determine how the quality of the solutions reflects on the users' attitude on SOM use.

The paper is organized as follows. In section 2, we briefly describe a review of the related literature. In section 3, we propose a framework for evaluating the visual data-mining tools from the user perspective. Section 4 describes the methods and procedures applied for evaluating the quality of use of the SOM tools. In section 5 we report the results obtained. Section 6 contains relevant discussion about our proposed evaluation framework and its generalizability. We conclude in Section 7 with final remarks and future work ideas.

2. Review of related literature

This section highlights few methods from the usability evaluation literature. It also looks into related studies regarding evaluation of the visualization tools.

2.1. Usability evaluation

Usability is defined in standard ISO/IEC 9126-1 as being the capability of the software product to be *understood*, *learned*, *used* and *attractive* to the user. Bevan (1995) refers to usability with the term *quality of use*. This reflects the extent to which the users can achieve specific goals with *effectiveness*, *efficiency*, and *satisfaction*.

Dix et al. (1998) point out that usability evaluation of the system is conducted in order to ensure that the system behaves in conformity with developers' expectations and users requirements. The evaluation methods are divided into four categories: analytic methods, specialist reports, user reports, and observational reports. The techniques corresponding to user-centric evaluation include experimental methods, observational methods, and surveys.

An example of survey instrument is the End-User Computing Satisfaction (EUCS), developed by Doll and Torkzadeh (1988). It measures the user satisfaction with both information product and ease of use items, using five sub-scales: content, accuracy, ease of use, format, and timeliness.

Another survey instrument is Software Usability Measurement Inventory (SUMI) for assessing user attitudes regarding software tools (Kirakowski 1994).

2.2. Evaluation of the visualization techniques

Tufte (1997) and Bertin (1981) provide us the bases for defining quality with regard to visualization. Card et al. (1999) point out the importance attached to the evaluation of visualization techniques. Moreover, according to Chen and Czerwinski (2000), the proliferation of visualization techniques also highlights the need for principles and methodologies for empirical evaluation of these techniques. However, relatively little research has been done in this area. Morse et al. (2000) propose a method for evaluation based on a visual taxonomy, intended to test the visualization in isolation from the rest of the system. Other studies are concerned with the effectiveness and utility of the tools (Stasko et al. 2000), or they are targeted to specific types of visualization (Risden et al. 2000, Sutcliffe et al. 2000).

In this paper, we are concerned with evaluating the quality of use of visual data-mining tools in order to assess the user satisfaction. We take into consideration all the relevant aspects of the system: visualization, interaction with the system, and information provided.

3. The framework for evaluating the quality of use of visual data-mining tools

The activities, in which the user is involved during the visual data-mining process, are depicted in Figure 1. To accomplish certain goals and tasks, the user employs the domain knowledge, and the data available in databases. The access to the data is allowed through data-mining systems. In essence, the visualization represents an interface to the data stored in the databases. For simplicity, we describe the way in which the human uses the system as follows. With a certain goal in mind, the user examines the visualization, interacts with it, and finally gets some information. The user satisfaction and, therefore, the success of the data-mining process depend on how good the visualization, the interaction and the information are.

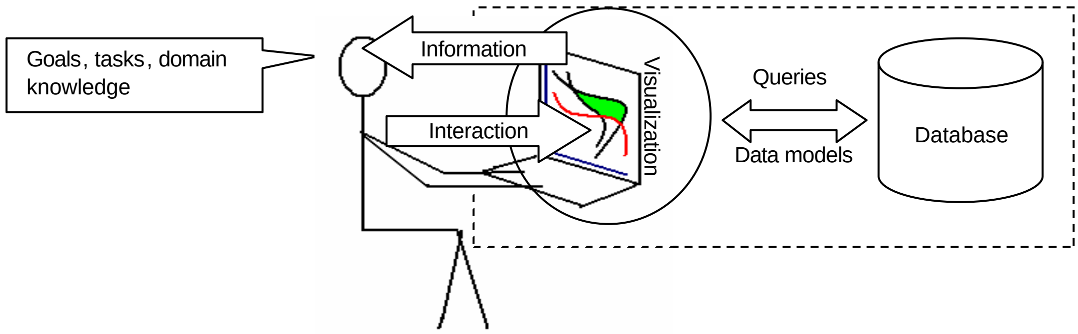


Figure 1. The relations between visualization, interaction and information in data-mining process

A *good visualization* properly represents the data of interest. The initial settings should be adequate and practical. The graphical design must convey structures and content of data. The visualization system should allow a variety of exploration tasks such as overview, details of data, and filter, to facilitate to the user the access to the desired information. Finally, the visualization should make the user to think about data, and allow the transfer of the results to other applications.

A *good interaction* with the system is ensured when the system is efficient, accurate, and easy to use and learn.

Regarding the *information*, this must be interesting, new, reliable and accurate.

3.1. Definition of terms

3.1.1. Quality of use

Quality of use of a visual data-mining tool is defined as being the totality of features and characteristics of the tool that reflect on its ability to satisfy the users' needs. In other words, quality of use reflects the satisfaction of the user with all features of the tool. As stated above, the main and direct features of the system, that influence the user attitude and behaviour, are: visualization of data, user-system interaction, and information obtained.

3.1.2. Quality of visualization

At this level we are concerned with evaluating the capability of the visualization system to transform the input data and make them accessible to the user. The issues to be evaluated are presented in Figure 2.

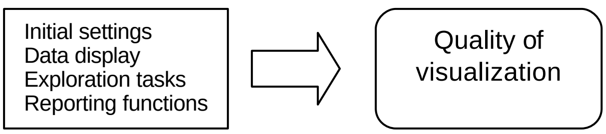


Figure 2. Evaluating the quality of visualization

- *Initial settings* refer to the requirements on input data format, the degree of data abstraction, and the setting of the parameters for visualization.
- *Data display* regards the possibility to visualize the data structure, data variation, data content, and data comparison. Moreover, the description, tabulation and decoration of data are important to evaluate.
- *Exploration tasks* include the five visual tasks identified by Shneiderman (1996), i.e. overview, details of data, filter, details on demand, and relate.
- *Reporting functions* represent those system functions that allow the user to transfer the results outside the application for various purposes. In this part we are concerned with

evaluating whether the user is satisfied with how s/he benefits from the visualization. We also ask whether the user is encouraged by the visualization to think of the data, rather than of the graphical design and methodology.

3.1.3. Quality of interaction

Assessing the quality of interaction is conducted in order to find out whether the users of the system consider the system easy to use and learn, accurate, effective and efficient. We classify the interaction attributes in five groups (Figure 3).

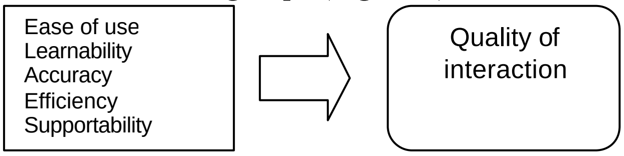


Figure 3. Evaluating the quality of interaction

- *Ease of use* stands for the characteristic of the system to be easy to control by the user and to provide the user with freedom of action (controllability and flexibility).
- *Learnability* affects how easy and fast the users feel that they master the system to perform the desired tasks.
- *Accuracy* (reliability) reflects the frequency and severity of system errors or failures.
- *Efficiency* measures the degree to which users feel that the software helps them in their work (to tailor frequent actions, improve working performance, and receive fast response to queries).
- *Supportability* regards the users' access to documentation and support, when needed.

3.1.4. Quality of information

Assessing the quality of information is meant to answer whether the users are satisfied with the output information provided by the system. Figure 4 shows the four attributes of information, which the user might require.

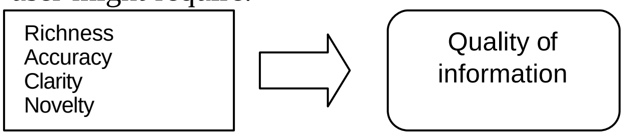


Figure 4. Evaluating the quality of information

- *Richness* of information stands for completeness, usefulness, and interestingness. Also it must correspond to users' needs and expectations.
- *Accuracy* of the information regards the degree to which the information is precise, correct, and consistent with users' knowledge.
- *Clarity* of information means that the information is presented in a clear and understandable way, and allows interpretation and inferences.
- *Novelty* of information reflects the characteristic of being new and up-to-date.

3.2. Relationships between attributes

The relationships between the attributes corresponding to the three levels of assessment are described in Figure 5.

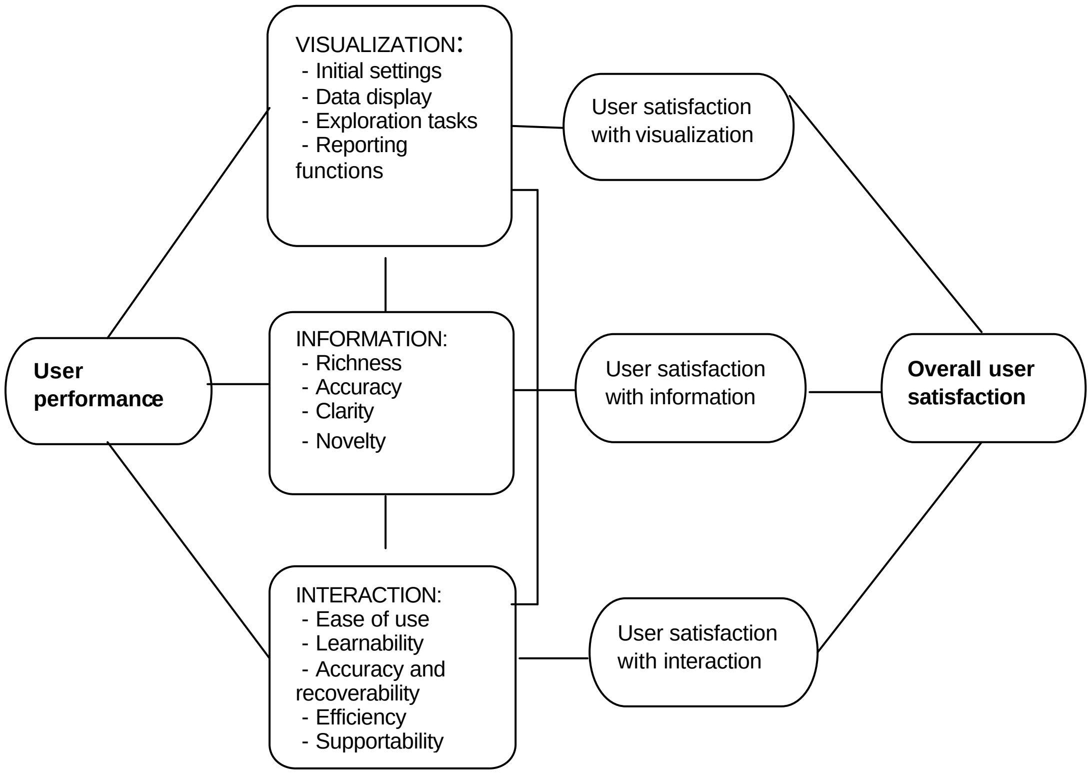


Figure 5. Relationships between attributes

When the user examines the data display, and uses the results, s/he must find the information being rich, accurate, clear, easy to interpret, novel and up-to-date. Moreover, whenever the user interacts with the system, s/he wishes the process to be easy, accurate, and effective.

4. Exploratory study: evaluating quality of use of the SOM tools

We employed the mixed methods research design in order to analyse the quality of the SOM tools, and also to get insight into the quality of the solutions the users found. For the quantitative part of the study, which concerned the quality of use of SOM tools, we used the questionnaire survey technique to collect data. In the qualitative part of the study, we were interested in analysing the participants' solutions to the task they were asked to solve.

4.1. Participants

The participants in our study were 26 students, enrolled for an Information Systems course, in a public university. The research site was the classroom. The demographics of the participants are presented in Table 1.

Table 1. Demographics of the participants in the survey

Category	Values	Percentage
Major	Information systems	61,54
	Computer Science	19,23
	Economics and Computer Science	11,53
	Mathematics	3,85
	Accounting	3,85
Years at university	1, 2 years	26,92
	3, 4 years	34,62
	5 and over	30,77
	Non response	7,69
Programming experience	Yes	80,77
	No	19,23
Data analysis experience	Yes	26,92
	No	73,08

4.2. Materials

In our study, we used three software packages, which implemented the SOM algorithm, all being available online for downloading. These were SOM_PAK, SOM Toolbox for Matlab, and Nenet (Kohonen 2001).

The data collection process consisted of the following phases: 1. the students were trained to use all three SOM tools, 2. they were asked to solve an assignment and report their findings, 3. after returning the solutions, the students were asked to answer the questionnaire.

The students had the possibility to choose the tools they wanted to work with, out of SOM_Pak, SOM Toolbox for Matlab, and Nenet. Nenet was definitely preferred by all students, for visualizing the maps, while different students used either SOM_PAK or SOM Toolbox to train the maps. We used the Binomial, and Chi-square tests (Siegel and Castellan 1988) to check whether there are differences in attitudes between users of the SOM_PAK and SOM Toolbox, but no significant differences were found.

4.3. The quality attributes

Based on the framework described in Section 3, we selected the attributes of SOM tools to be evaluated (Figures 6, 7, and 8).

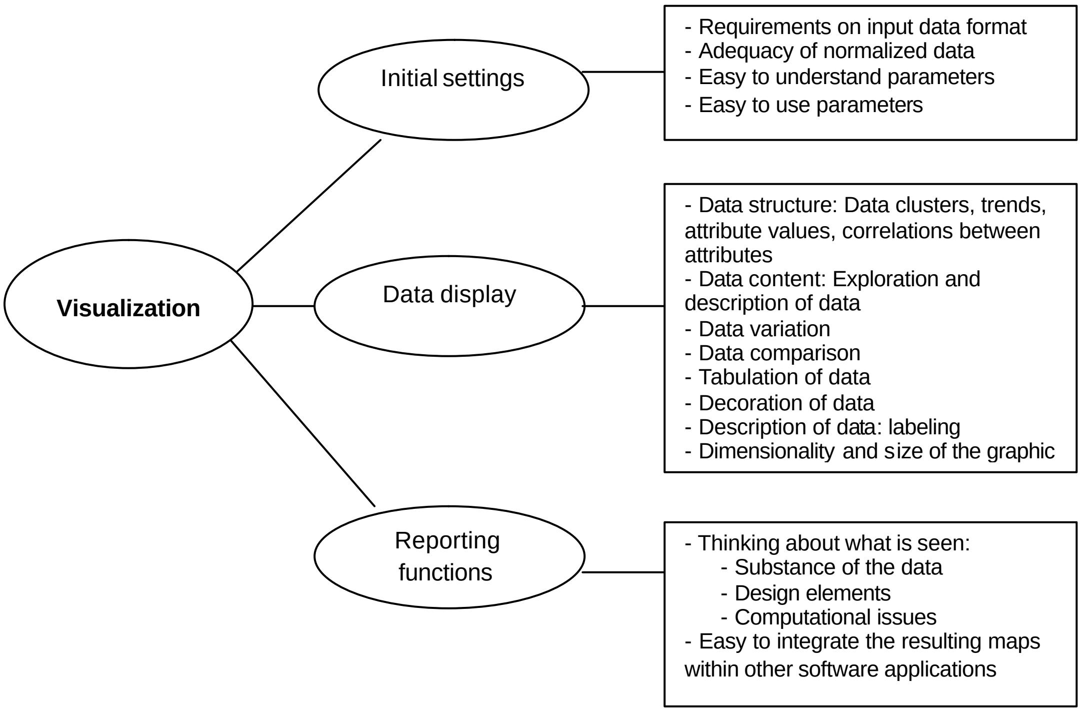


Figure 6. Attributes of visualization

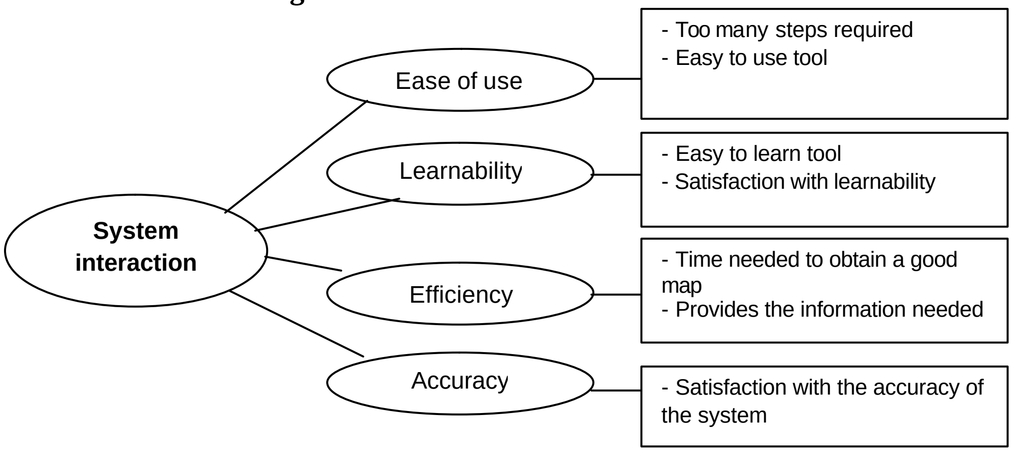


Figure 7. Attributes of interaction with the tool

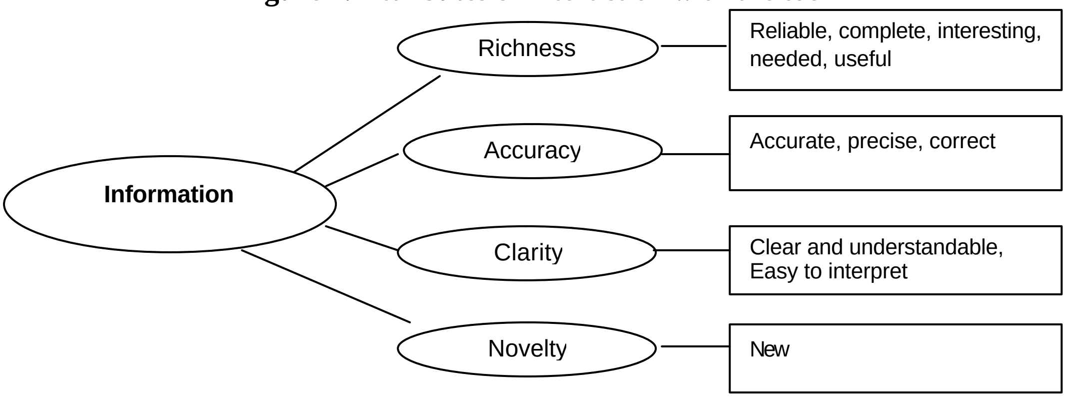


Figure 8. Attributes of information

5. Results

5.1. Quality of use of SOM tools

Figure 9 depicts the opinions regarding the *quality of visualization*. Among the positive features, we observe the good visualization of data clusters (92% respondents agree), the visualization of the comparable data and data trends.

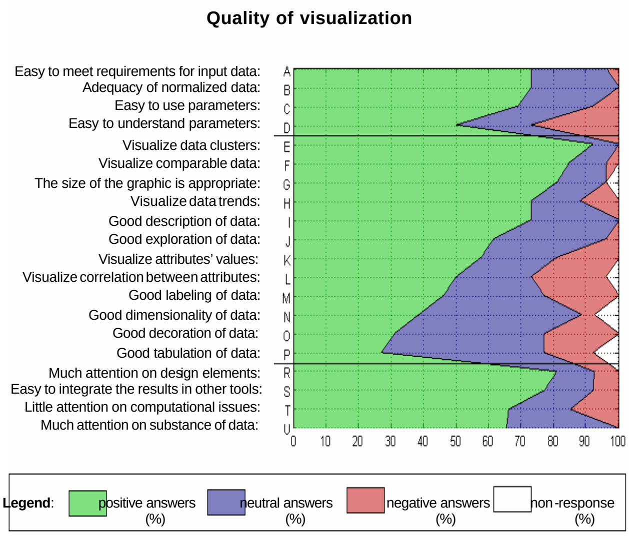


Figure 9. Quality of visualization. A – D: Initial settings, E – P: Data display, R – U: Reporting functions

The initial settings did not reveal major problems. However, the SOM parameters were found easy to understand only by 50% of students. Regarding the data display features, relatively low scores are noticed for tabulation of data, decoration of data, visualization of the correlations between attributes, and visualization of the attributes values. At the reporting functions category, we observe that more than 75% of participants found easy to use the results within other applications, and the attention of the users was focused on the substance of data for more than 65% of participants.

We asked a number of questions about the degree to which different design elements helped in interpreting the visualization (map). The answers are presented in Table 2.

Table 2. Assessment of the SOM's graphic elements

	Helpful			Adequate		
(%)	Agree	Neutral	Disagree	Good	Medium	Poor
Colors	92	8	0	88	12	0
Scales (color bars)	85	15	0	85	15	0
Grids, neurons, borders	81	19	0	57.5	31	11.5
Attribute values	69	19	8	54	31	15
Data labels	77	15	8	61.6	19	19.4

Figure 10 presents the opinions and attitudes regarding the *quality of interaction*. Among the positive interaction features are the ease of use, and ease of learning. Also, most of the users (82.60%) agreed that the system provided the information needed. The weak points perceived by the students are system flexibility (54% respondents agreed that there are too many steps required to get a good map), and efficiency (only 27% respondents were satisfied with the time needed to get a good map).

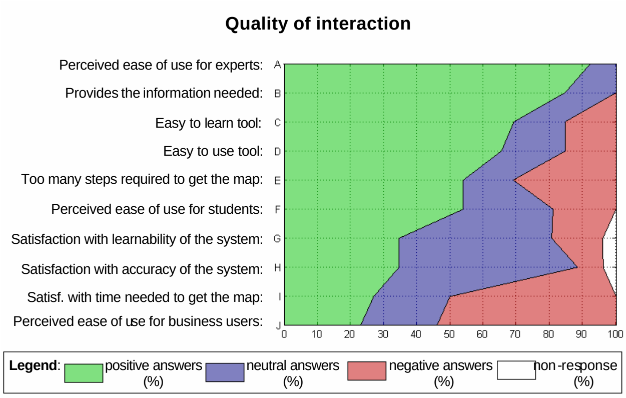


Figure 10. Quality of interaction

Figure 11 shows that the *information* obtained is helpful and useful in data analysis. It is also interesting, easy to understand, and complete for most of the students. However, these are not very satisfied with the correctness of the information and even less with its preciseness. Users still find the SOM content reliable, and overall the satisfaction with the content is high.

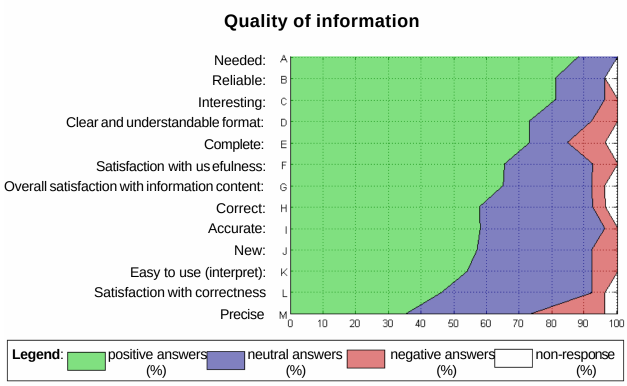
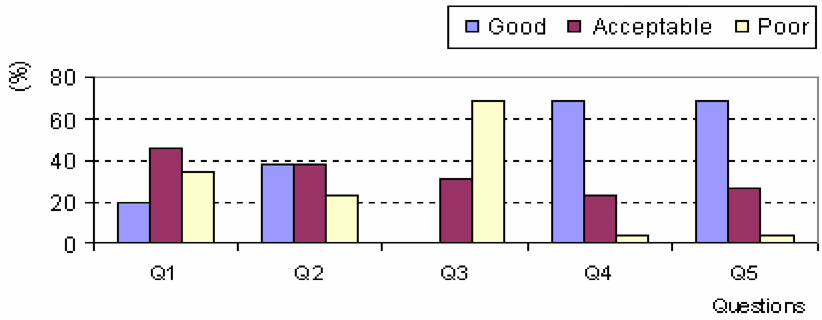


Figure 11. Quality of information

5.2. User performance

Participants in the experiment were asked to solve a complex task with SOM tools, namely to train the SOM until they obtain a map and with its help to answer five questions. For evaluating the user performance we analysed the students' reports describing the solutions found.

Figure 12 shows that the most difficult for students was to obtain an appropriate map on which to identify correct clusters. The first three questions, concerning the number of clusters and their definitions, received the most varied answers and these were not very well argued. Students themselves were aware that their map might not be the correct one, and noticed that an inappropriate map could lead to misinterpretations and mistakes in the decision making process. The last two questions are obviously much better answered.



Q1: How many clusters do you identify and what are the characteristics of each cluster?
Q2: Which is the cluster that contains the best performers in the market?
Q3: Which is the cluster that contains the worst performers in the market?
Q4: Discuss the performance of three specific companies based on their positions on the map and compare the results with the real data from the file provided.
Q5: Benchmark five specific companies one against the other, based on their positions on the map.

Figure 12. Quality of solutions reported by participants

Among the explanations the users gave to their imperfect solutions were the inexperience of working with SOM tools, the unfamiliarity with financial ratios, and the highly subjective criteria to separate the clusters (for some managers some ratios are more important in a certain time, etc.). Overall, the participants found it very interesting and useful to work with the SOM technique. It must be noticed that even 92% of the students were satisfied with the visualization of the data clusters, only 62% of the students gave acceptable and good solutions for that task (question Q1).

5.3. SOM tools limitations

Table 3 shows the main limitations of the SOM tools pointed out by our study. For each identified problem we propose possible solutions and suggestions to improve the software that implements SOM, in addition to those stated by Kohonen (2001).

Table 3. Problems found and suggestions for improvement

Problem	Suggestion for improvement
Level 1: quality of visualization - Not very easy to understand input parameters - Poor tabulation of data - Poor decoration of data - Medium data labelling	- Automation of parameters selection according to the input data characteristics and the desired results, - Enhance the "Details on demand" feature to display properly the input data and their statistics in tabular reports.
Level 2: quality of interaction - Low perceived ease of use for business users - Medium satisfaction with the time needed to get a good map (visualization), too many steps required - Medium satisfaction with the accuracy of the system - Medium satisfaction with the learnability of the system	- Provide automatic delineation of the clusters. - Due to the fact that SOM reduces the dimensions of the input space, the loss of accuracy is inevitable, but new learning algorithms could be tested for implementation.
Level 3: quality of information - Not very precise - Not high satisfaction with correctness - Not very easy to use (interpret) - Not very accurate	- Add explanations to the information displayed when these are requested.

6. Discussion

6.1. Consistency of the measurements

In order to examine the reliability of the scales that we used in assessment, we have computed the Cronbach's alpha coefficient. A rule of thumb states that the internal consistency of the scales is acceptable when alpha is greater than 0.7. Table 4 presents the Cronbach's alpha values for our data. At the Visualization level, there are lower values of alpha for Initial settings construct and Reporting functions. This is due to the fact that the questions in this section of the questionnaire were focused on distinct issues, so that no significant similarities in answering were found. Also, the six satisfaction questions that we used were not highly related and the corresponding Cronbach's alpha is relatively low. These low values are justified by the small number of items used, because the value of alpha increases directly with the number of items of the construct and also with the correlation between the items.

Table 4. The Cronbach's alpha computed for each level of assessment

Level	alpha	Notice	alpha
Visualization quality	**0.7724**	when graphical aspects are included:	**0.8704**
Initial settings	0.3971		
Data display	0.7273	when graphical aspects are included:	0.8704
Reporting functions	0.5659		
Interaction quality	**0.6739**	including visualization items:	**0.7046**
Ease of use and learning	0.6143	including visualization items:	0.6774
Accuracy	not computed, only one item used		
Efficiency	not computed, only one item used		
Information quality	**0.7467**	including visualization items:	**0.8748**
Richness	0.5443	including visualization items:	0.7732
Accuracy	0.6075		
Clarity	0.6110		
Novelty	not computed, only one item used		
Satisfaction questions	**0.6291**		
All quality questions	**0.8872**	using the three-point scale, derived from the original five-point scale	
User Performance	**0.7044**	for the scores we assigned to the solutions offered by students	
Overall	**0.8845**	user performance and quality questions	

6.2. Interdependencies between attributes

For exploring the interdependencies between variables, we performed an exploratory factor analysis, based on the extraction of the principal components (PC). Applying this technique to the data revealed us that only a selected number of variables were to be retained as significant. Table 5 presents the variables that show a high contribution in the variance of the data corresponding to each level of assessment.

Table 5. The most contributing variables in evaluation

Level	PC	Cumulative variance of rotated components (%)	Most significant variable in the rotated component	Weight in rotated component
Visualization	1	13.217	Data labels adequacy	0.897
	2	24.957	Colours helpfulness	0.853
	3	33.475	Tabulation of data, Dimensionality of data	0.817 0.820
	4	41.707	Description of data	0.873
	5	49.613	User performance items (Q2), but also Q5	0.695
	6	57.266	Adequacy of normalized data	0.854
	7	63.524	User performance (Q4)	0.759
	8	69.171	Easy to understand parameters	0.823
	9	74.408	Attention on data representation, Data attributes representation	0.661 -0.817
	10	79.504	Data clusters visualization	0.816
	11	84.546	Requirements on data format	0.813
Interaction	1	18.868	User performance (Q5)	0.861
	2	33.782	Easy to use tool	0.920
	3	47.353	Easy to use for students	0.835
	4	59.111	Satisfaction with accuracy	0.841
	5	70.469	Efficiency	0.872
Information	1	16.978	Easy to interpret	0.809
	2	28.988	User performance (Q5), but also Q1, Q2, Q4	0.777
	3	40.547	Completeness	0.884
	4	51.626	Usefulness	0.815
	5	61.411	Correctness	0.751
	6	70.670	Novelty	0.906
	7	79.109	User performance (Q3)	0.801

We also explored the correlations between the variables derived from the factor analysis. For example, it resulted that the user performance is interdependent with the ease of use of the tool (correlation coefficient = 0.42), preciseness (0.44), clarity (0.401), visualization of the data attributes correlations (0.488), visualization of the data variations (0.488), adequacy of the data labels (0.423). Other notable correlations are: attention on data representation is correlated highly with tabulation of data and adequacy of data labels.

The evaluation framework we presented can be generalized by using the approach for generalizing from theory to description. According to Lee and Baskerville (2003) this type of generality involves generalizing from theoretical statements to empirical (descriptive) statements. The framework can be applied with small variations from the present format in different settings, and with different visualization techniques or visual data-mining tools.

Regarding the method for assessment, we recommend the user-centric approaches. The user-centric approaches to qualitative evaluation employ a representative number of people out of the actual or potential users of the software tool. One method for collecting the data from these people is the survey. The survey technique is appropriate for our problem because it is designed to assess the relative frequency, distribution, and interrelations of naturally occurring phenomena in the population under study.

7. Conclusions

We developed a framework for evaluating visual data-mining tools, and we examined the satisfaction of the users with SOM tools. The framework consists of three levels of evaluation: visualization, interaction, and information. These levels are not completely separated, but interdependent.

To examine the applicability of the framework, we conducted an exploratory study for evaluating the quality of use of the SOM tools. Quality of use was defined as being the satisfaction with all the features of the SOM software, namely visualization of data, interaction with the system, and information obtained. The results showed that the users were satisfied working with SOM tools. Most of the visual features were considered helpful and adequate. People were helped by the SOM technique to understand and analyze relatively large amount of data and to obtain interesting and new information. Regarding the interaction with the tools, participants in the study found the tools easy to use and learn. Nevertheless, the SOM tools appear to have also weak points. These are identified in terms of "too long time needed to obtain a good map", relatively low accuracy, preciseness, and correctness of the information, difficulty in interpreting the results. All these shortcomings, especially the lack of efficiency and preciseness might be explanations of why business users do not use frequently the SOM tools in financial data analysis.

The significance of the study is twofold. Firstly, we provided a comprehensive framework for assessing the visual data-mining tools from the user perspective. Secondly, the study offers insights into the use of the SOM tools, from data collected through a survey questionnaire and multiple case studies. These insights into how people effectively use and think about the SOM tools can help developers of complex commercial applications in visual data mining to gather new and interesting information about the tool, its users and their needs.

A limitation of the study is that the sample used in the exploratory study does not represent the target population (business users), but students. This drawback might be compensated by the fact that the students worked on a real life problem and real data. Moreover, the sample size is relatively small.

For future we aim to test thoroughly the applicability of the evaluation framework, by examining other tools. Moreover, the causal relationships that the framework reveals remained unexplored and we intend to conduct formal experiments in order to explore them fully.

8. References

Back, B., Öström, K., Sere, K., and Vanharanta, H. (2000) "Analyzing Company Performance Using Internet Data", *Proceedings of the 11th Meeting of the Euro Working Group on DSS*, Ed. by Zaraté, Toulouse, France, pp52-56

Bertin, J. (1981) *Graphics and Graphic Information Processing*, Walter de Gruyter, New York.

Bevan, N. (1995) "Measuring usability as quality of use", *Software Quality Journal*, Vol. 4, No. 2, pp115-130.

Card, S., Mackinlay, J., and Shneiderman, B. (1999) *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann, San Francisco.

Chen, C., and Czerwinski, M. (2000) "Empirical evaluation of Information Visualizations: an introduction", *International Journal of Human-Computer Studies*, Vol. 53, pp631-635.

Dix, A., Finlay, J., Abowd, G., and Beale, R. (1998) *Human-Computer Interaction*, Second Edition, Prentice Hall.

Doll, W.J. and Torkzadeh, G. (1988) "The measurement of end-user computing satisfaction", *MIS Quarterly*, Vol. 12, Issue 2, pp259-274.

ISO/IEC 9126-1 (2001) *Software Engineering, Product quality, Part 1: Quality model*, International Standards Organization.

Kaski, S., Kangas, J., and Kohonen, T. (1998) "Bibliography of Self-Organizing Map (SOM) papers 1981-1997", *Neural Computing Surveys*, pp102-350.

Kaski, S. and Kohonen, T. (1996) "Exploratory Data Analysis by the Self-Organizing Map: Structures of Welfare and Poverty in the World", *Proceedings of the Third International Conference on Neural Network in the Capital Markets*, World Scientific.

Kirakowski, J., (1994) "The Use of Questionnaire Methods for Usability Assessment" [online], http://www.ucc.ie/hfrg/questionnaires/sumi/index.html, last accessed June 2nd 2004.

Kohonen, T. (2001) *Self-Organizing Maps*, Third Edition, Springer.

Lee, A.S., and Baskerville, R.L. (2003) "Generalizing Generalizability in Information System Research", *Information Systems Research*, Vol.14, No.3, pp221- 243.

Morse, E., Lewis, M., and Olsen, K.A. (2000) "Evaluating visualization: using a taxonomic guide", *International Journal of Human-Computer Studies*, Vol. 53, pp637-662.

Oja, E., Kaski, S., and Kohonen, T. (2003) "Bibliography of Self-Organizing Map (SOM) papers: 1998-2001 Addendum", *Neural Computing Surveys*, 3, pp1-156.

Risden, K., Czerwinski, M.P., Munzner, T., and Cook, D.B. (2000) "An initial examination of ease of use for 2D and 3D information visualizations of Web content", *International Journal of Human-Computer Studies*, Vol. 53, pp695-714.

Shneiderman, B. (1996) "The Eye Have It: A Task by Data Type Taxonomy for Information Visualizations", *Proceedings of Visual Languages* (Boulder, CO, September 3-6). IEEE Computer Science Press, Los Alamitos, CA, pp336-343.

Siegel, S., and Castellan, N. J. (1988) *Non-Parametric Statistics for the Behavioral Sciences*, Second Edition, McGraw-Hill.

Stasko, J., Catrambone, R., Guzdial, M., and McDonald, K. (2000) "An evaluation of space-filling information visualizations for depicting hierarchical structures", *International Journal of Human-Computer Studies*, Vol. 53, pp663-694.

Sutcliffe, A.G., Ennis, M., and Hu, J. (2000) "Evaluating the effectiveness of visual user interfaces for information retrieval", *International Journal of Human-Computer Studies*, Vol. 53, pp741-763.

Tufte, E. R. (1986) *The Visual Display of Quantitative Information*, Graphics Press, Cheshire, Connecticut.