

December 2006

A GDSS for Visualizing and Assessing a Technology Environment

Jan Ondrus

University of Lausanne- Switzerland

Jean Monzani

University of Lausanne- Switzerland

Yves Pigneur

University of Lausanne- Switzerland

Follow this and additional works at: <http://aisel.aisnet.org/amcis2006>

Recommended Citation

Ondrus, Jan; Monzani, Jean; and Pigneur, Yves, "A GDSS for Visualizing and Assessing a Technology Environment" (2006). *AMCIS 2006 Proceedings*. 209.

<http://aisel.aisnet.org/amcis2006/209>

This material is brought to you by the Americas Conference on Information Systems (AMCIS) at AIS Electronic Library (AISEL). It has been accepted for inclusion in AMCIS 2006 Proceedings by an authorized administrator of AIS Electronic Library (AISEL). For more information, please contact elibrary@aisnet.org.

A GDSS for Visualizing and Assessing a Technology Environment

Jan Ondrus

University of Lausanne, Switzerland
jan.ondrus@unil.ch

Jean-Sébastien Monzani

University of Lausanne, Switzerland
jean-sebastien.monzani@unil.ch

Yves Pigneur

University of Lausanne, Switzerland
yves.pigneur@unil.ch

ABSTRACT

The basic premise of this paper is that a multi-actor multi-criteria decision-making approach, supported by a highly-visual tool, is a strong candidate for assisting technology assessment and forecast. The analysis should involve multiple actors from different industries and embed various perspectives in order to have a more complete picture of the technology environment. To support this activity, we designed a GDSS that facilitates interaction with experts during the elicitation of preferences. Moreover, emphasis was placed on enhancing visualization of the input data and outcomes, which could be highly appreciated when conducting a distributed and unsynchronized Delphi study. In this paper we illustrate the application of this tool in the context of the Swiss mobile payment industry.

Keywords

GDSS, data visualization, multi-criteria decision-making, technology assessment.

INTRODUCTION

Technology assessment and foresight are complex activities as they involve multiple perspectives and therefore a large amount of data to process and visualize. Multi-criteria decision-making (MCDM) methods are considered strong candidates to support this type of analysis (Salo et al., 2003 p.251). As the input of some MCDM methods are matrices of evaluation, implementations were easily done in spreadsheets. However, the manual data input process is not always very effective. Moreover, the visualization capabilities of spreadsheets are rather limited. Therefore, the development of standalone software could offer great opportunities to customize the graphic user interfaces in order to enhance data collection process and visualization.

In our research to assess and forecast the Swiss mobile payment market, we selected Electre I (Benayoun et al., 1966) with a group decision feature (Bui and Jarke, 1984), which enabled us to integrate the analyses of multiple actors. The amount of collected data to compute in Electre I becomes large as more experts join the analysis. Therefore, we designed a GDSS (PylaDESS) that is capable to handle numerous actors and therefore, a great number of input matrices. Moreover, emphasis was placed on enabling the visualization of the data from different perspectives. The outcomes obtained with Electre I are outranking matrices and graphs. In order to fully exploit the collected data and enrich the analysis, we added some modules of visualization. These features significantly enhanced the understanding of the results derived with Electre I by helping to uncover the preference discrepancies between the participating actors. This was particularly necessary given that the disparity of evaluations meant that there was no group consensus.

Our research objective is to design an IT artefact which supports the needs for visualizing and assessing a technology environment. We developed the tool using an iterative and incremental approach. We conducted two consecutive rounds of interviews in Switzerland using a MCDM approach based on Electre I. At each stage of our analysis, we improved our tool according to our needs. In the first development phase, we focused on improving the data collection process by implementing the “Pack of card” technique (inspired by Simos, 1990 and improved by Pictet and Bollinger, 2003) to help the elicitation of preferences and automatic data input process. In the second phase, we concentrated on the visualization of the data to enrich the analysis.

In our research context, the mobile payment industry, the IT artefact significantly improved the understanding of the results obtained with Electre I. Despite the abundance of data, various modules that aggregate the information in clear graphics ease visualization.

In the next section of this paper we briefly introduce the context and application of our research in the mobile payment market. Then we present the data input and its collection process. Further, we describe the implementation of Electre I and its group decision feature. The following section will expose some examples of data visualization within our IT artefact. Then, we propose an evaluation and a short comparison of related work. Finally, a last section we conclude with a discussion of our contribution.

USING AN MCDM APPROACH IN THE MOBILE PAYMENT INDUSTRY CONTEXT

Despite the multitude of barriers hindering their deployment, mobile payments are still seen as a natural evolution of payment processes by most experts. The great uncertainty surrounding this market has led to many speculations. Current understanding of the situation is relatively unclear, even among industry insiders. The Swiss mobile payment case is particularly interesting in terms of its actors. The financial institutions have great clout and expertise in the payment industry. However, mobile network operators (MNOs) own the mobile network infrastructure and have a large customer base that is less segmented (i.e. 3 national MNOs versus more than 150 banks). Merchants, especially retailers and public transportation companies, could also play an important role in terms of point of acceptance and volume of transaction. Given the number of actors, the analysis should involve experts from different industries to obtain multiple relevant perspectives. For this reason, we extended Electre I with a group decision feature proposed by (Bui et Jarke 1984).

The objective of this research is to assess the Swiss mobile payment market in a holistic manner. To decompose the analysis problem, we identified two potential disruptions that could occur in the mobile payment market. The first was a technology-based disruption (i.e. a shift from card-based to phone-based solutions) and the second was an organization-based disruption (i.e. a switch from a dominant operator-driven to a more self-organized solution). We used various methods such as interviews, the Delphi technique, and MCDM method to analyze the factors enabling or disabling the two disruptions.

We conducted three consecutive rounds of interviews in Switzerland over the past two years. In order to obtain a broader overview of the market, we interviewed relevant experts working for different industries, including financial institutions, mobile network operators, retailers, public transportation companies, and technology providers. The diversity of experts facilitated market analysis from multiple points of view. We used an MCDM approach during the two last rounds. The preliminary results of the second round can be found in (Ondrus and Pigneur, 2006).

During the interview campaigns, we were guided by the hypothesis that MCDM methods are suitable for strategic technology assessment and foresight. There are a relatively high number of parameters to consider in order to have a complete picture of the market. We believe that a multi-actor MCDM approach could respond to our needs as MCDM methods are largely concerned with the deployment of systematic methods to help address problems characterized by incomparable objectives, multiple stakeholders and conflicting interests (Stewart, 1992). Moreover, Salo et al. have suggested the use of multi-criteria methods for technology foresight and concluded that there is potential "*in terms of lending rigour and transparency to foresight process*" (Salo et al., 2003).

To support this approach, we designed (built and evaluated) a GDSS (PylaDESS) which enables us to use a structured and formal model. Our systematic approach consists of modeling the problem, building a tool to support the analysis, and evaluating the pertinence of this tool in a real environment. This research follows a design science research paradigm as described in (March and Smith, 1995).

We contend that Electre I, as an MCDM method, is well adapted for the problem at hand. MCDM methods usually imply a modeling activity, which should clarify many aspects, making the decision process more transparent. Electre I (Benayoun et al., 1966) allows the decision maker to select the ideal technology with a maximum of advantages and a minimum of inconveniences in the function of various criteria. ELECTRE I gives the possibility to model a decision making process by using the concordance and discordance indexes and the outranking relations. The concordance index measures the degree of dominance of one action over another, based on the relative importance weightings of the decision criteria. The discordance index measures the degree to which an action is worse than another. In summary, concordance and discordance indices can be viewed as measurements of satisfaction and dissatisfaction that a decision maker senses when choosing one action over another. The outranking relations are usually obtained with a combination of a high level of concordance and a low level of discordance. These levels are fixed by a concordance and a discordance threshold which can be seen as severity levels over and under which an action could outrank another.

In our mobile payment case study, one primary objective was to unveil the technological preferences of the various experts. Thanks to the group decision feature of the GDSS, we were also able to find the industry consensus. We involved about 15 experts but contrary to our expectations, no consensus was found. This was mainly due to the disparities in the experts' evaluations. Therefore, we decided to further search for potential consensus inside individual industries by filtering the experts by "families" (i.e. companies working in the same industry), which yielded interesting results.

The GDSS supports activities at different stages of our approach. During the data collection process, there is a highly interactive module which is a computerized card game to insert the data directly in the model. The description of this module is done in the next section. For the analysis, the GDSS facilitates the processing real-time results, which could be constantly computed from the evaluations matrices. The interactivity is enhanced as the feedback is immediate, enabling us to conduct "what if" sensitivity analyses. Moreover, there are many different pop-up windows to analyze the data from different perspectives. Some interesting visualization features of our GDSS will be depicted in a further section.

In a design science research, one activity is to validate the IT artefact. It is usually done by verifying the alignment between the requirements analysis and the evaluation of the IT artefact operating in a real environment. This will be done in the section about the evaluation of our GDSS.

THE INTERACTION DURING THE DATA INPUT PROCESS

In this section, we describe the methodology used to interview the mobile payment experts and how we collected data from them.

The first part of the interviews was to introduce our research and explain the data collection process to the experts. Then, we asked them to choose a set of criteria to evaluate the technologies. To help them, we showed them a list established by previous experts. They could add or remove criteria from the list depending on the aspects relevant to them. Each expert built a customized set of criteria to evaluate some technology alternatives. Each criterion was described with a standardized definition, eventually understood the same way by each expert.

Once they finished building their own set of criteria, they had to select each criterion from a list to start the card game. Using the computer, the experts had to rank the criteria by importance. The most important criteria are placed on top and those less important on the bottom of the screen (see Figure 1).

The weights are calculated in real-time using the "Pack of Card" technique (Simos, 1990; Pictet and Bollinger, 2003). When the experts were satisfied with the relative weight of each criterion, they could validate the ranking.

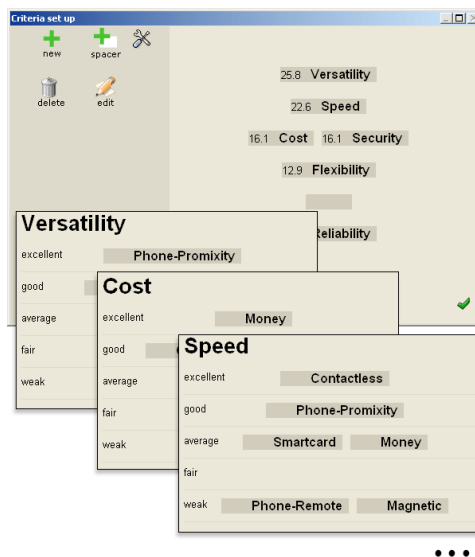


Figure 1. Card game

The next step was to elicit the preference of the experts by using a verbal scale varying from weak, fair, average, good to excellent. The experts had to place the cards on the scale for each criterion. The data collection ended when evaluations were made for each selected criterion. With this done, we could run the computation of the model and show the results to the experts. We usually started a discussion to check that the experts were satisfied and understood the results obtained.

The manual card game was not the most effective method to collect the data. As we acquired experience during our second round of interviews, we adapted our tool for the third round accordingly. We computerized the card game so the data could be inserted automatically. Moreover, the results could be found in real-time which improved interaction with the experts. We received a very positive feedback from experts who participated in both the manual and computerized game of cards, noting improvements in terms of interaction, clarity and speed.

Besides the card game, we also added some visualization and computing features. The information given by the outranking graphs was not entirely satisfying. The richness of the data we obtained was not fully used. Because we felt that the data should be entirely exploited, we developed some modules to data cross-analysis with weights and evaluations. This tool allows a comparison of the evaluation of all the experts in different graphs. As discussed before, there are also some filters to display only the experts from a particular industry. The objective of this feature was to discover if there were any industry-wide patterns (i.e. if experts from the same industry have similar evaluations).

IMPLEMENTING THE ELECTRE METHOD

In this section, we present the implementation of Electre I in our GDSS. PylaDESS was developed with Python programming language and wxWidgets cross platform GUI library. PylaDESS was mostly developed on MS Windows and a Mac OS X version of PylaDESS is used during the interviews. Therefore, we can confirm that PylaDESS runs on multiple platforms (not tested with Linux). The Electre I formulas implemented in this prototype can be found in (Ondrus and Pigneur, 2006). Due to space limitations, we could only depict a selection of visualization graphs in the next sections.

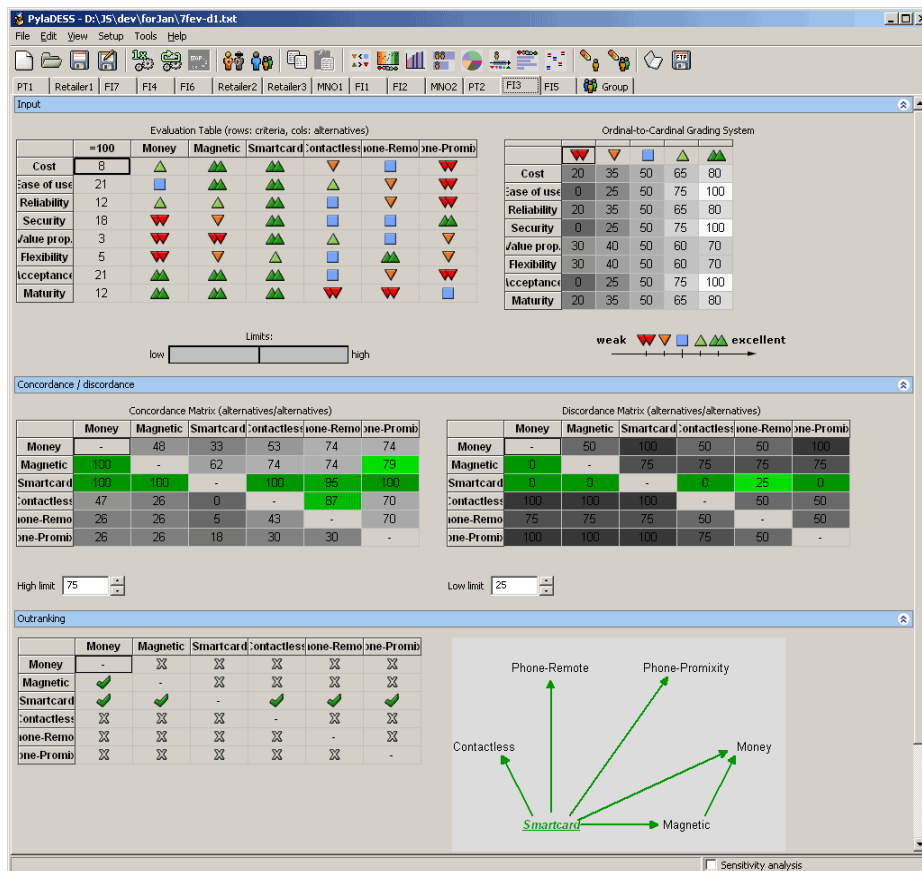


Figure 2. The PylaDESS user interface

User Interface Design

The PylaDESS user interface (see Figure 2) is divided into different windows and tabs as analysis of the problem can quickly become complex. The main window comprises, for each actor, the evaluations and the corresponding concordance, discordance and outranking matrices. Another tab is devoted to analyze the group of actors (i.e. the group decision feature and other visualization tools). This interface enables a rapid modification of data and direct observation of the resulting changes. Deeper investigations of specific issues can also be performed on demand with dedicated pop-up windows. These features are presented in the next sections.

PylaDESS represents each actor's evaluations in separated tabs (under the toolbar) of the main application window (see Figure 2). Each tab is separated into horizontal sections that can be temporarily hidden for better flexibility and visibility. The first section stores the weights and evaluations of actors (collected with the card game) in a matrix. Criteria are located in rows and alternatives in columns. The evaluation scale has five steps ranging from *weak* to *excellent*. Rather than representing them with digits between 0 to 4, we favored a logotype to improve the situation overview. A stronger visual signal is achieved by combining shapes and colors. An *average* evaluation is a blue square, while the positive and negative evaluations use green and red tones, respectively evaluations are also associated with shapes representing triangles pointing down for negative and up for positive evaluations. One green triangle pointing up would be *good* whereas two darker green triangles would be *excellent*. These evaluations can be modified directly in the matrices. Similarly, the ordinal-to-cardinal grading system represented on the right is also modifiable to suit the analysis.

Outputs of Electre I are concordance, discordance and outranking matrices. Each of them can be visualized in the last two sections of the actor's tab. Adjustable severity thresholds for concordance and discordance (usually 75% and 25%) will have a direct influence on the outranking matrix and graph. When values comply with the conditions of outranking (e.g. the concordance: equal or more than 75; discordance: equal or less than 25), the color of the cell turns green. The stronger the value the darker green the cell will be. This color sensitivity facilitates differentiating between the important values. The outranking matrix and graph is a combination of concordance and discordance matrices, the outranking graph improve the representation of the outranking matrix. Alternatives are represented in a circle. An arrow between an alternative *a* and alternative *b* indicates that *a* outranks *b*. Underlined italic labels distinguish alternatives that are never outranked from others. They represent the kernel of the “best” solutions. As an illustration, the actor represented on the screenshot (Figure 2) prefers the *SmartCard* to the other alternative. There is also a preference of *Magnetic* over *Money*.

Furthermore, it is possible to compute Electre I results either on demand or continuously (by clicking on the corresponding buttons located in the toolbar or selecting an option from the menu). This enables a “what if” sensitivity analysis capability as it gives almost instantaneous feedback. Any modifications in the evaluations have direct repercussions on the results and automatically display the new outcome. A quicker analysis could be done by launching the *Limits Comparison Graph* (see Figure 4), described in the next section.

DATA VISUALIZATION WITH PYLADESS

Graphs and representations

We categorized the various graphical representations proposed by PylaDESS into two families:

- **Visualization of input matrices:** As actors' evaluations are inserted in matrices on different tabs of the interface, proposing various pairwise representations of the data could be very helpful. These graphs are useful when it comes to comparing actor evaluations, which are usually represented on different pages (i.e. tabs). With the help of these graphs, it is possible to represent all the actors' evaluations and weights for a specific pair of criterion and alternative. This offers at a quick view of how good the alternative is and how important the criterion is for all actors.
- **Specific combined analysis:** In addition to the outranking graphs of Electre I, many graphs in PylaDESS try to combine and represent data from different perspectives. Some examples are illustrated with Figures 3 to 6. Moreover, we implemented another MCDM algorithm, the Weighted Sum Model (WSM) proposed by Fishburn (1967). This method calculates a ranking directly from the evaluation and weights, which confirms results obtained with Electre I and add more useful information about the preferences.

As this research grew, more actors were added to the model, which offered more opportunities for a finer analysis by *clustering actors of the same industry into families*. In the current system, a family is assigned to each actor (actors can also be independent). Filtering functions update the graphs to limit the analysis to only a specific subset of actors. This feature is demonstrated in the *Proximity Map* of Figure 3B. This map represents the alternatives and the actors on a 2D plane (see

Figure 3). Actors are closer to the alternatives they prefer. The distance function relies on the evaluations and on the alternatives weighted by their importance for each actor. The map is computed by the algorithm presented by Quinn (1979). Actors and alternatives, represented on a 2D map, are linked by invisible “springs” or “forces” and dynamically arrange themselves. Skupin and Fabrikant (2003) suggest that proximity data can be effectively translated into spring models.

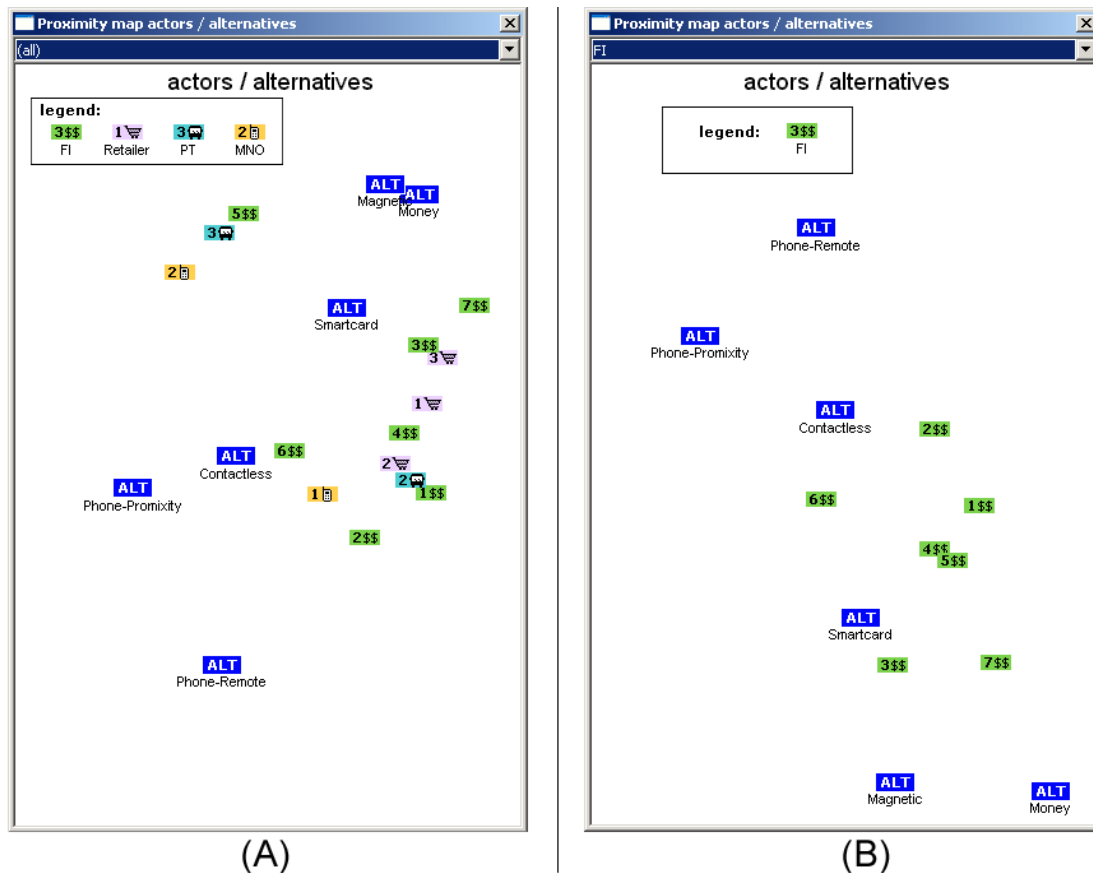


Figure 3. The Proximity Maps for (A) all actors and (B) for the Financial Institutions

The *Proximity Map* is illustrated in Figure 3 with our mobile payment study, which in this case, is a technology-based disruption analysis. Different icons represent the four families of actors (i.e. Financial Institutions, Retailers, Public Transportation, and Mobile Network Operators) with numbers to identify each actor anonymously. The general *Proximity Map* (Figure 3A) gives an overview of how all actors are placed respectively to alternatives (i.e. [ALT] icons). For instance, the “Financial Institution 2” (i.e. [2 \$\$] icon on the bottom right) has a preference for the “Contactless” and “Phone-Remote” alternatives, but clearly stays away from “Magnetic” and “Money”. As the number of actors grows, it could become more complicated to read the *Proximity Map*. Thus, we can filter the actors by family, as represented on Figure 3B with the “Financial Institutions” family. As can be seen, the financial industry prefers card-based to phone-based solutions.

Comparison of Limits and Evaluations

Actors’ evaluations could have a direct impact on the outranking matrices. When analyzing the problem, an actor might not be sure about an evaluation. For instance in Figure 4, the expert evaluated an alternative/criterion (i.e. Smartcard/Speed) as *excellent* (on the *weak, fair, average, good, excellent* scale). A slight modification of the evaluation could influence the outcome. Therefore, computing the robustness of an evaluation could be very useful (i.e. the limits in which the evaluations do not change the outcome).

The *Limits Comparison Graph* automatically computes all of the limits for a specific actor and presents them in a matrix of graphs. This matrix gives an instant overview of evaluations and their impact on the outcome (see Figure 4). It is also

possible to compare the position of the selected actor with the average evaluation of the whole group and its family. This could be very useful to detect the evaluations that are hindering the attainment of a consensus. These evaluations could be errors or diverging positions, which could also simply show disparities of knowledge between the actors.

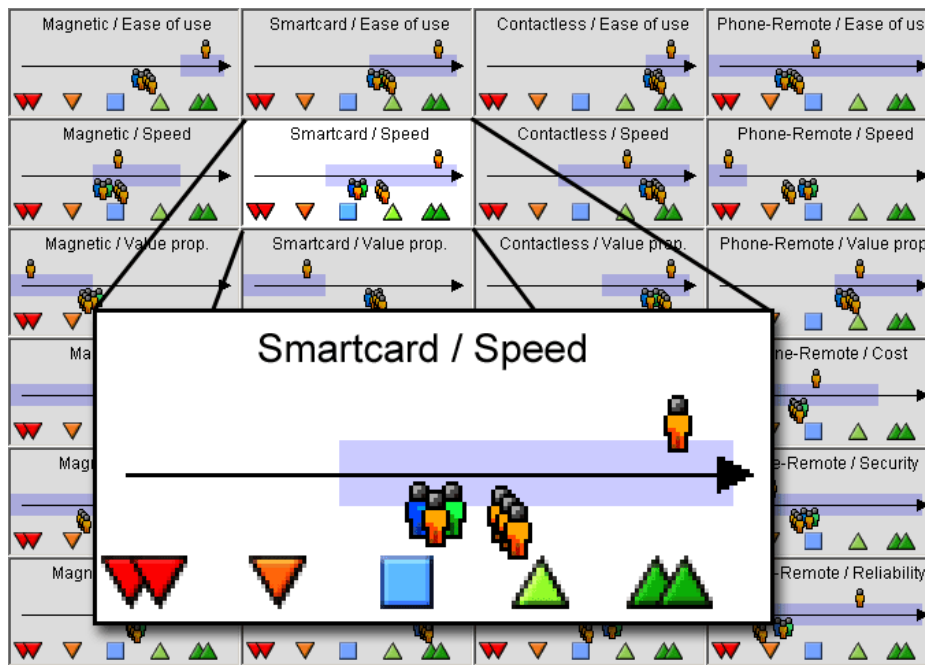


Figure 4. Comparison of limits

We have enlarged the evaluation for the *Smartcard* alternative and *Speed* criterion. The *weak* to *excellent* scale is represented horizontally (with our regular logotype). The filled bar painted over it indicates the range of evaluations that will not affect the outcome (a *fair* evaluation would change the outranking matrix). The evaluation of the actor (the icon on the top right) is *excellent* (two triangles) while the average evaluation of its family (same industry) is almost *good*. The whole group evaluated the speed for smartcard as *average*. Despite the differences of evaluations, this figure indicates that the position of the actor is quite robust, as the interval of possible changes covers the two other average evaluations.

A similar matrix of graphs is also available for comparing evaluations (Figure 5). Actors are grouped by their evaluations for a criterion and an alternative. The graph is vertically sliced into zones devoted to each evaluation (scale), and while weight of the criteria is a function of its height on the graph (i.e. the higher the position, the more important the criteria is for the actor). This graph could facilitate the identification of industry patterns derived from the evaluations. For instance, Retailers 1 and 3 evaluated the reliability of phone-proximity as *fair*. Moreover, reliability is considered as an important criterion to both of them. On their side, the public transportation companies evaluate the reliability of phone-proximity as *good* with less weight for the criterion. Details are easily zoomed by clicking on the small graphs located in the matrix.

Average weights for criteria

In our approach, actors were free to define their own criteria to evaluate alternatives, which is usually not the case in MCDM methods. As PylaDESS keeps a list of all criteria entered in the system, we could rank criteria by the average of the weights given by the experts. In order to determine the average weights, we sum the individual weights and divide the total number of actors using the criterion. The *Average Weights* window displays a list of all criteria, together with their average weight in percentage (see Figure 6). This average weight is combined into a bar graph with a series of actor icons which indicate the number of actors who used the criterion. The criteria are ranked using the average value and the number of actors. This directly gives an ordered global list of the most important criteria.

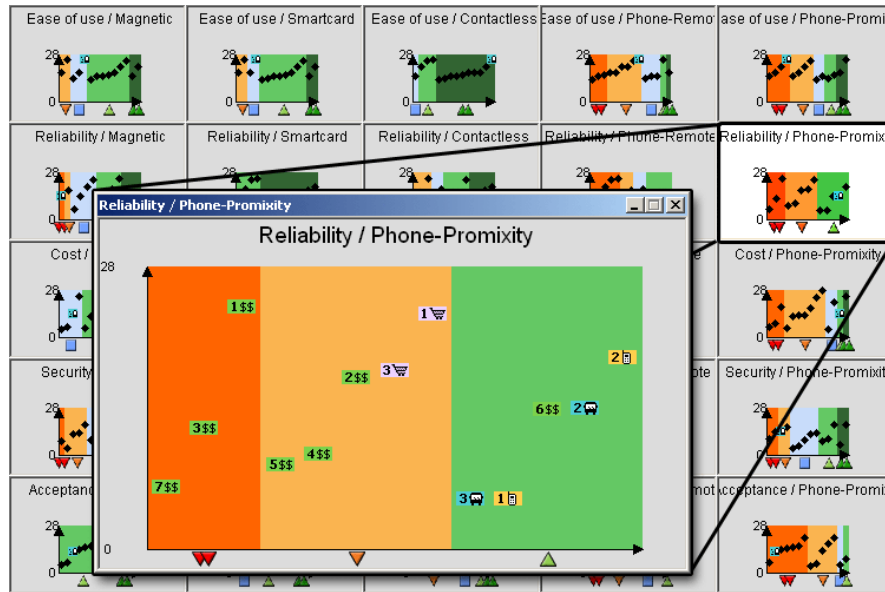


Figure 5. Comparison of evaluations

With an average weight of 18%, *Ease of use* is the most important criteria found for our technology assessment, followed by *Cost* and *Reliability*. On the very bottom of the window, the *Versatility* might be considered as important with an average weight of 18%, but only one actor used it.

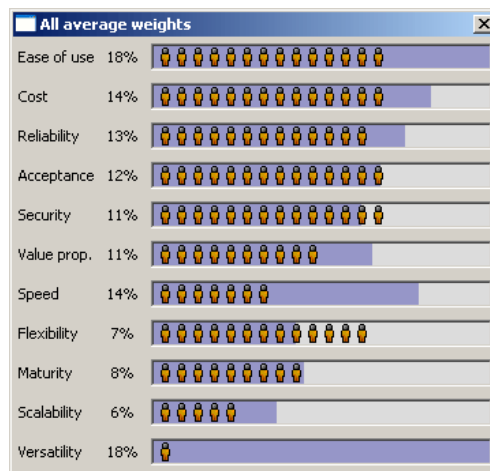


Figure 6. Average weights for criteria

EVALUATION, RELATED WORK AND CONTRIBUTION

The use of our GDSS in a real context allowed us to evaluate its relevance. The mobile payment market is challenging to assess due to the complexity of the current situation. Thanks to the GDSS, we were able to confirm and better understand some trends currently observed in the market. For instance, we obtained clear results that support the dominance of card-based payment solutions. This preference was noticeable in outranking graphs and proximity maps. Moreover, as we added visualization of the data from multiple perspectives, we discovered interesting trends which will be presented in upcoming research paper. By using this GDSS and the MCDM methodology, we were able to exploit a more structured approach to study the two potential disruptions in the mobile payment market.

As we conducted three rounds of interviews, we could perceive improvements from using this GDSS for our interview process. The first round consisted of semi-open question interviews. We did not have any tool to analyze the qualitative data.

In the second round, we had a functioning version of the GDSS but with limited features. Finally, during the third round we were able to fully take advantage of the GDSS in each stage of the analysis (i.e. interview process, analysis, and visualization).

The use of the GDSS to support our analysis was very helpful in many aspects. During the data collection process, the interactivity with the experts was improved, compared to the use of the physical card game. Moreover, the duration of the data input process was shortened. The fact that the results could be obtained during the same interview also generated satisfaction from the experts. Feedback in real-time greatly enhanced the discussions about the results. Some sensitivity analyses could also be conducted to test the robustness of some evaluations when the experts were not satisfied with their results. Therefore, their understanding about the whole analysis improved. During our global analysis process, the GDSS facilitated visualization of the results and data. Without the help of the GDSS, it would have been difficult to process all the data collected for each experts, compare and filter the results. Moreover, we obtained very promising results using our approach backed up with the GDSS. This encourages us to continue exploiting this approach.

We tested several DSS and GDSS implementing Electre I and other MCDM methods before we started our analysis. None of the tools fully corresponded to our needs. We therefore decided to develop our own tool based on the requirements we had due to the constraints for our analysis. We constantly tested and improved it as our needs evolved, especially for the data collection process and the visualization of the data input and results.

We compared to PylaDESS a non-exhaustive list of DSS and GDSS software including Co-oP (Bui, 1987), IDEAS (Vetschera, 1988), Linam (Wieser, 1993), Electre III/IV (Roy, 1991), IRIS2 (Dias and Mousseau, 2003), Decision Lab (Brans and Mareschal, 1994) and Macbeth (Bana e Costa et al. 1997). In summary, there were two generations of software. Some tools were developed to only compute results with limited visualization and interaction (e.g. Linam, IDEAS, Co-oP), whereas others were meant to display the results with more advanced visualization interfaces (e.g. Macbeth, Decision Lab, IRIS2). Because of its features, PylaDESS belongs to a new generation GDSS as it provides a nice interactive user interface that facilitates the data input process and provides real-time computing, improved visualization of input data and outcomes and sensitivity analysis. Some of these characteristics were found in the other software, but none of them comprise all the features at once.

CONCLUSIONS

By designing and using PylaDESS, we improved the visualization and the assessment of mobile payment phenomena in Switzerland. Moreover, PylaDESS allowed us to explore and demonstrate the unrevealed potential of MCDM methods for technology strategic assessment, here illustrated in the Swiss mobile payment context. Much emphasis was placed on enhancing visualization of the data input and outcomes, something which could be highly appreciated when conducting an anonymous, distributed, and unsynchronized Delphi study. Thus far, we have also had encouraging results in our research of clarifying the picture of the mobile payment industry in Switzerland by identifying and analyzing two potential disruptions (one technological and one organizational) with multiple perspective approaches (not exposed in this paper, see Ondrus and Pigneur, 2006).

ACKNOWLEDGMENTS

The work presented in this paper was supported by the National Competence Center in Research on Mobile Information and Communication Systems (NCCR MICS), a center supported by the Swiss National Science Foundation under grant number 5005-67322.

REFERENCES

1. Bana e Costa, C., Stewart, T., and Vansnick, J.-C. (1997). Applications of the MACBETH approach in the framework of an additive aggregation model. *Journal of Multi-Criteria Decision Analysis*, 6(2):107–114.
2. Benayoun, R., Roy, B., and Sussmann, B. (1966) Manuel de référence du programme electre. *Note de synthèse, formation n.25, Direction scientifique SEMA, Paris*.
3. Brans, J. and Mareschal, B. (1994). PROMCALC and GAIA: a new decision support system for multicriteria decision aid. *Decision Support Systems*, 12:297 – 310.
4. Bui, T. (1987). *Co-oP: A Group Decision Support System for Cooperative Multiple Criteria Group Decision Making*, volume 290 of *Lecture Notes in Computer Science*. Springer-Verlag, Berlin.

5. Bui, T. and Jarke, M. (1984) A DSS for cooperative multiple criteria group decision making. *International Conference on Information Systems (ICIS)*.
6. Dias, L. and Mousseau, V. (2003). IRIS: A DSS for multiple criteria sorting problems. *Journal of Multi-Criteria Decision Analysis*, 12(4-5):285–298.
7. Fishburn, P. C. (1967). Additive utilities with incomplete product set: Applications to priorities and assignments. *Operations Research Society of America (ORSA), Baltimore, MD, USA*.
8. March, S. T. and Smith, G. F. (1995) Design and natural science research on information technology. *Decision Support System*, 15(4):251–266.
9. Ondrus, J. and Pigneur, Y. (2006) A multi-stakeholder multi-criteria assessment framework of mobile payments: An illustration with the Swiss public transportation industry. *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06), IEEE Computer Society*.
10. Pictet, J. and Bollinger, D. (2003) Adjuger un marché au mieux-disant. analyse multicritère, pratique et droit des marchés publics. *Presses polytechniques et universitaires romandes, Lausanne*.
11. Quinn, N., and Breuer, M. (1979) A force directed component placement procedure for printed circuit boards. *IEEE Transaction on Circuits Systems*, 26, 6, 377-388
12. Roy, B. (1991) The outranking approach and the foundations of ELECTRE methods. *Theory and Decision*, 31:49–73.
13. Salo, A., Gustafsson, T., and Ramanathan, R. (2003) Multicriteria methods for technology foresight. *Journal of Forecasting*, 22(2):235–255.
14. Simos, J. (1990) *Evaluer l'impact sur l'environnement*. Presses polytechniques et universitaires romandes.
15. Skupin, A., and Fabrikant, S.I. (2003) Spatialization methods: a cartographic research agenda for non-geographic information visualization. *Cartography and Geographic Information Science*, 30, 2, 95-115.
16. Vetschera, R. (1988) An interactive outranking system for multi-attribute decision making. *Computers and Operations Research*, 15(311-322).
17. Wieser, P. (1993) Linam software. EPFL, Switzerland.