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A Foresight Support System Using MCDM Methods

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Abstract In this paper, we demonstrate the design and use of a foresight support system (FSS) combining two multi-criteria decision-making (MCDM) methods. Traditionally, foresight activities involves Delphi, focus group, or Estimate–Talk–Estimate techniques to collect opinions of an expert panel. Often, these techniques are not computerized and data visualization is rudimentary. Our highly-interactive FSS solves a number of inherent issues during the data collection, analysis, and results visualization processes. Despite that MCDM methods have been recommended for technology foresight, a validation with a real field experiment was still required. To evaluate our approach and FSS, we conducted a foresight exercise for the Swiss mobile payments market. Our research confirms that the use of MCDM methods supported with a computerized tool can enhance the foresight processes and results.

Keywords Foresight support systems · Technology foresight · MCDM methods

1 Introduction

Due to the rapid pace of technology innovation, the business environment of firms has become increasingly variable, complex, and uncertain (Camponovo et al. 2005).

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One critical issue in IT management is to face emerging technologies (McKeen and Smith 2003). This challenge requires to adopt a systematic process to stay up-to-date and evaluate new technology for a potential integration within the organization to yield economical benefits (Martin 1995). Firms have to assess their environment to understand the external forces of change that may affect their future position so that they can develop effective responses (Aguilar 1967). The importance of obtaining a holistic perception of the environment has been advocated by numerous prominent authors in the strategic management discipline (e.g., Bourgeois 1980; Learned et al. 1969; Porter 1998). They see co-alignment between the firm and its environment to be essential for performance.

The assessment of future technology evolutions and discovery of weak signals traditionally relies on various forecasting approaches. Often, these approaches use trends extrapolation. Unfortunately, these approaches are only appropriate when the uncertainty level is sufficiently low (Courtney et al. 1997). Moreover, they fail to consider the possibility that actors in a system could influence the evolution of their own environments, thus causing possible discontinuities with the past (Godet 1979). In contrast, popular scenario approaches have been conceived to address high levels of complexity and uncertainty (Dyson 1990). However, they are often difficult to coordinate given the lack of precise methodology and supporting tools (Salo and Gustafsson 2004).

In common settings, a panel of experts is formed to discuss possible future trends. To structure discussions and analyses, the group generally recourses to techniques such as Delphi (Linstone and Turoff 1975), focus group (Basch 1987), and Estimate–Talk–Estimate (Gustafson et al. 1973). A weakness of these qualitative techniques is the poor support of computer-based tools. The data collection, analysis, and outcome visualization processes are rather limited as the scalability of these methods is insufficient to integrate large quantity of data. Because of the inherent nature of the technology foresight process, there are a relatively high number of parameters to consider in order to obtain a more complete picture of the situation. Other management tools and techniques have been proposed in the scientific community and the literature (e.g., scenario planning, technology roadmap, ROI, real option) but few of them have been widely adopted by companies (Danese and Kalchschmidt 2011; Zotteri and Kalchschmidt 2007). In many cases, it seems that there is a real lack of interactive and visualization tools for technology foresight activities (Kuesters et al. 2006; Bañuls and Salmeron 2011). More emphasis has been given to organizational matters than the instrumental aspects (Bañuls and Salmeron 2011; Salo et al. 2003).

This paper demonstrates a way to enhance technology foresight processes using two multi-criteria decision-making (MCDM) methods supported by a computerized tool. In this study, we present the design of a group decision support systems (GDSS) which aims at facilitating foresight processes. Researchers recently referred to these systems as foresight support systems (FSS) (Bañuls and Salmeron 2011; Markmann et al. 2012). Our FSS was designed in order to support data collection, computation, and visualization. It combines two complementary MCDM methods: ELECTRE I (Benayoun et al. 1966) and the Weight Sum Model (Fishburn 1967). During the design process, a special focus has been given to interactivity and visualization. Following the design science research evaluation guidelines provided by Venable et al.

(2012), we evaluated the approach and the tool in a real environment with a number of industry actors. The field study's objective was to assess and foresight trends for the Swiss mobile payments market. We identified two types of possible evolutions: (i) a technology-based and (ii) an organizational-based. To study these two evolutions, we involved an exhaustive set of experts working for different industries in Switzerland.

Our research contributes to the extant literature on several fronts. First, although prior research has claimed that MCDM methods are good candidates for technology foresight (Salo et al. 2003), they have not been fully explored in real-world settings. In this study we present an approach combining two complementary MCDM methods that are suitable for running and improving such exercise. Second, we designed and tested a FSS to address the scarcity of MCDM computer tools available. Third, we propose and evaluate nine design propositions to improve the foresight processes with MCDM methods. Fourth, we introduce new ways of unveiling and visualizing weak signals with a computer tool. Fifth, we evaluated our design in real settings with experts dealing with a complex problem at hand (i.e., the development of the Swiss mobile payment market). Overall, this research extends the MCDM and decision support systems domains as it provides an original design and a real evaluation for an alternative application (i.e., technology foresight).

In the next section, we discuss related research and identify some of the issues that we want to solve with our approach. In Sect. 3, we present our design propositions. To evaluate the approach, Sect. 4 describes our field experiment conducted for the Swiss mobile payment market. Section 5 discusses some limitations inherent to our research project. Lastly, Sect. 6 concludes the paper with some discussions and proposes further research.

2 MCDM Methods for Technology Foresight

To support foresight activities, different methodologies have been proposed. A paper from the Technology Futures Analysis Methods Working Group (2004) reviews 50 methods that aim at either compiling information or seeking to understand interactions among events, trends, and actions. These methods are either "hard" (quantitative: empirical, numerical) or "soft" (qualitative: judgmentally based, reflecting tacit knowledge). Despite the broad number of methods, common standard practices and features are shared. In most cases, it is advised to mix both quantitative and qualitative approaches. They complement each other well and compensate their possible weaknesses. Of course, the choice of the method greatly lies on the availability of the data (Fildes et al. 2006), which explains the multitude of methods available. The Technology Futures Analysis Methods Working Group (2004) does not prescribe specific methods for certain foresight problems. Instead, the group lists a number of limitations that need to be taken into account when selecting a method. For example, experts opinion methods are affected by what people perceive as feasible (due to limited imagination). Quantitative forecasting models sometimes assume linear relationships among variables while interaction could be multivariate and result in non-lineralities. Other identified issues are related to time horizon, degree of complexity, and uncertainty. In the same line, Bendahan et al. (2004) claims that the vast majority of the methods and techniques proposed are either inappropriate, too complex, or over-simplistic, hence unusable. Thus they fail to deal appropriately with the rising complexity of the reality they represent. Consequently, methods and tools must be simple enough to be usable, while being sufficiently complex to match as closely as possible the variety of problems they intend to model.

By definition MCDM methods are excellent candidates to deal with complex problems (Petkov et al. 2007). MCDM methods imply a modeling activity, which clarifies many aspects. Salo et al. (2003) claim that MCDM methods offer potential “in terms of lending rigor and transparency to the foresight process”. Moreover, they argued that one of MCDM incontestable strengths is the theoretical foundation, which is an advantage compared to the work that has previously been done in technology foresight. MCDM methods are largely concerned with the deployment of systematic processes to help address problems characterized by incomparable objectives, multiple stakeholders, and conflicting interests (Stewart 1992).

MCDM methods are not used to find the optimal solution (like a mathematical programming model) but rather try to determine what solution is the closest to be “optimal” in regards of several criteria or among existing solutions. Bui (1984) described two key features that characterize MCDM methods. First, MCDM methods allow to analyze a problem with several criteria simultaneously and concurrently. Criteria can be either quantitative (e.g., cost, weight) or qualitative (e.g., quality of service, beauty). Criteria usually conflict with each other. In other words, the improvement of one criterion can only be done at the expense of another. Second, MCDM methods allow to consider experts’ subjective evaluations by letting them express their preferences by evaluating the alternatives and weighting the criteria.

Roy (2005) explains that the use of MCDM methods is not limited to solving a problem of choice. He describes four non-exhaustive alternatives. *The description problematic* does not seek to elaborate any prescription or recommendation but instead could just consist of a set of potential actions, a family of criteria and additional information about the decision problem. The *choice problematic* aims at selecting the smallest number of “good” actions that are usually non comparable with one another. The *sorting problematic* seeks to assign each action to the most appropriate category. In this case, the categories are not necessarily ordered. Finally, the *ranking problematic* compares actions between one another. Further, he adds that adopting one of them is in most cases not sufficient to found a prescription or recommendation.

Three distinct phases of the decision have been characterized by Simon (1955). These are intelligence, design, and choice. Bui (1984) argued that MCDM methods usually focus on the two last phases. However, MCDM methods have been found in different fields of application. Other authors discussed the use of MCDM methods, such as AHP for making predictions (Bhushan and Rai 2004; Dyer et al. 1988). Yet, Salo et al. (2003) claims that MCDM methods have not been fully explored in technology foresight. They justified this phenomenon because of the recent emergence of technology foresight activities. Moreover, it seems like more attention in the literature has been given to organizational matters and less to methodological questions.

In addition to the existing MCDM features, the Technology Futures Analysis Methods Working Group (2004) argues that a multi-actor approach is desirable for technology foresight. Multi-actor approaches apply to situations where multiple actors are confronted with a number of issues whose the evolution in the future is uncertain and difficult to foresight (Bendahan et al. 2004). Such situations could be found in contexts where various actors have different goals or preferences on the different alternatives under discussion. Another situation is a scenario where actors could play a key role in the evolution of the current situation by influencing a number of key evolutionary variables. To achieve a better understanding of these situations, methods should take into account the preferences of all relevant actors and the interrelationship between them (Bendahan et al. 2004).

Another important feature to take into account during foresight activities is the time dimension. Rafii and Kampas (2002)' instrument is one of the few existing MCDM framework that was proposed for technology foresight. They introduce a time dimension (i.e., stages) to take into account the dynamic perspective needed for a technology foresight exercise. Rafii and Kampas intend their simple tool to be used in a situation where a dominant actor (incumbent) might be threatened by an insurgent but does not know the real impact. Unfortunately, the use of Rafii and Kampas' instrument has several weaknesses. The instrument is rather limited for multi-actor usage. Scalability is therefore particularly hard to achieve. As only two alternatives can be compared at a time, this technique prevents to conduct a more holistic analysis. In terms of outcome, the evaluation is superficial and needs finer granularity to fully grasp the phenomenon studied. In brief, Rafii and Kampas framework is only suitable for getting an overview of a given situation. More precise data and outcome are required to better understand complex problems.

Despite Salo et al. (2003)' claim and our arguments that MCDM methods are good candidates for technology foresight activities, a demonstration and validation in real settings are still required. In the next sections, we propose the design and use of an integrated MCDM approach supported by a FSS that aims at increasing the efficiency and effectiveness of technology foresight activities as it simplifies and streamlines the data collection, computing, and visualization processes.

3 Design Propositions: Towards an Integrated Multi-perspective Approach

In this section, we elaborate nine implementable design propositions to enhance technology foresight activities. The main objective is to fulfill the multi-criteria, multi-actor, and multi-stage dimensions requirements. Using a MCDM process view to illustrate MCDM methods (Bui 1984), we structure our propositions with the traditional Input–Tool–Output relation (see Table 1). Our design propositions aim at aligning our design to this process and enabling computer-support for each stage of it.

Table 1 Requirements of an integrated multi-perspective approach

	INPUT	TOOL	OUTPUT
Multi-criteria	Collect data	Compute data	Visualize results
Multi-actor	Support scalability	Aggregate data	Compare results
Multi-stage	Allow flexibility	Analyze robustness	Store scenarios

The *INPUT* comprises three important components: (i) the alternatives, (ii) the criteria, and (iii) the decision-maker preferences (i.e., the evaluations and weights). The alternatives are the possible solutions or actions for a particular decision problem. The criteria are the different aspects under which alternatives can be evaluated. The preferences are the evaluations of the alternatives under a criterion. The weights are the relative importances or priorities of the criteria for the decision-maker.

The *TOOL (computation)* is the collection of methodologies the analyst needs in order to use MCDM methods. The methodologies can be very formalized or heuristic depending on the type of problem to solve.

The *OUTPUT* are the results obtained by the MCDM methods. This results are usually synthetic and could be represented in varied forms such as rankings, zero-one matrices and graphs.

3.1 INPUT: Facilitating the Experts' Preference Elicitation

The formulation of alternatives belong to the first step when building an MCDM model. Often, alternatives are established by a subset of experts. The selected alternatives are then fixed in the model and shared among all experts. Next, experts choose a set of criteria to evaluate the alternatives. The relative weight of each criterion is also established in order to take into account how important the experts judge the criterion to be. When the initial MCDM model is built, the data collection process can begin with the elicitation of experts' preferences. In other words, the experts evaluate each alternative for each criterion.

During this INPUT process, several problems have to be fixed. Depending on the number of alternatives and criteria, MCDM methods could require to collect a rather large amount of data from the expert. As a result, the process becomes quite repetitive. During a field experiment, the time granted by the experts (e.g., executives) is usually short. Experts can become impatient with a repetitive input method. The tedious process for preference elicitation has to be quick and enjoyable. Second, in a foresight process the number of experts involved can be large. The classic data collection processes for MCDM methods need to be scalable. Third, the preference elicitation can happen in different settings. For example, experts can be met individually in a sequence or all simultaneously in the same room. The data collection methods have to offer some versatility.

In order to solve the three exposed problems in the INPUT process, we describe three design propositions. First, we propose to computerize the data collection and make the process quicker and more enjoyable. Second, we suggest to enable the possibility to integrate as many individual MCDM models as required. Third, we recommend adequate options to enter evaluations into the individual MCDM models.

3.1.1 Design Proposition I: Computerized Tool for Facilitating the Data Collection

To avoid collecting data with a repetitive survey, the use of the "Pack of Cards" technique proposed by Simos (1990), later improved by Pictet and Bollinger (2003), can ease and speed up the MCDM data collection process. Cards of each criterion and

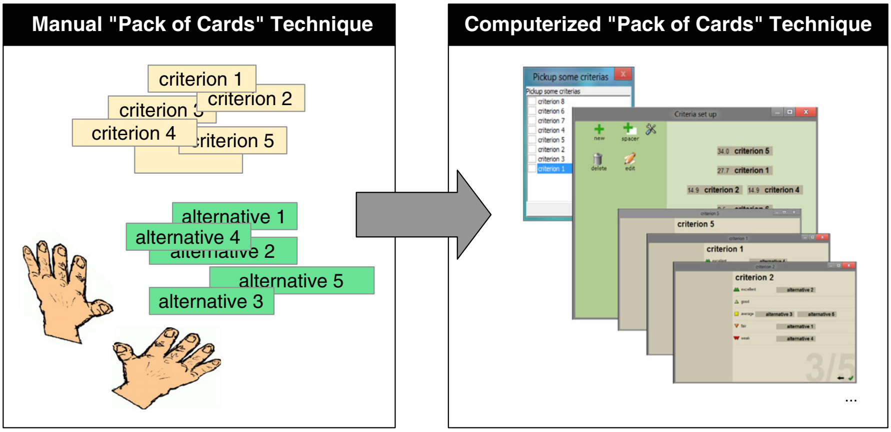


Fig. 1 The computerized "Pack of Cards" technique

alternatives are given to experts. Experts are allowed to add or remove any criterion at the beginning of the process. Once the set of criteria is defined, experts rank criteria in order of importance to derive the weights. The next step is to group and rank alternatives for each criterion. Finally, experts assign an evaluation (e.g., weak, fair, average, good, excellent) to the different groups of alternatives. In addition to the improved efficiency of the process, the active participation in the procedure gives experts a more intuitive understanding of the approach (Rogers et al. 2000).

Due to the more enjoyable data collection process, we propose to adopt the manual "Pack of Cards" technique as well as some improvements (see Fig. 1). The weights are calculated automatically in real-time by the computer once the ranking is done. Then, sequentially, experts evaluate alternatives in light of the criteria by using the verbal scale varying from weak, fair, average, good to excellent. Once the evaluation step is done, the software automatically enters data in the MCDM model and computes the results. There is no manual input required.

To display the evaluations of the alternatives, the criteria, and their respective weights, an editable matrix contains all the data collected (see Fig. 2). The criteria are listed in the first column in the left, sorted by importance (weight). The second column contains the weight given to each criterion. The total weight of 100 has to be spread among all the criteria. The first row lists the alternatives. Then, at the intersections of rows and columns, we find the scores (i.e., evaluations, preferences). The evaluations are based on a five-value scale (i.e., weak, fair, average, good, excellent). Each value is represented by a different shape and color. The different shapes are helpful for "black and white" printing and color-blind people.

3.1.2 Design Proposition II: Support Scalability to Include as Many Experts as Needed

As technology foresight activities calls for the participation of multiple actors, our approach should allow to collect data from numerous experts for the same analysis.

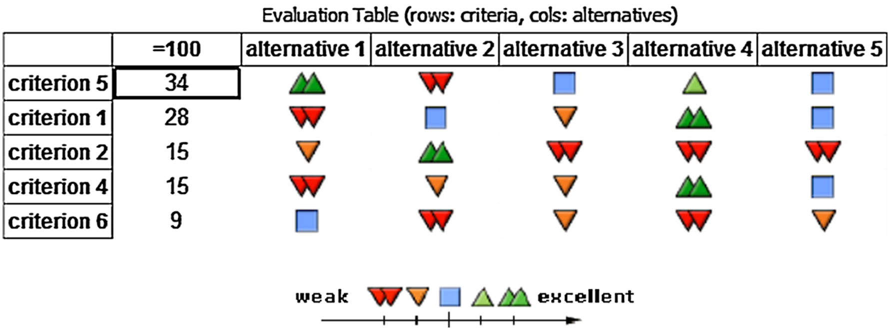


Fig. 2 Data input matrix

The tool should support data collection as well as data modification for each expert. The scalability of the tool is important as any additional MCDM model added in the overall analysis could provide interesting insights.

3.1.3 Design Proposition III: Allow Flexibility to Use in Different Settings

The data collection process could be done in asynchronous (individual meetings) or synchronous (experts workshop) manners. The “Pack of Card” technique is well-suited for face-to-face data collection for the creation of one single MCDM model. When meeting experts sequentially, the “Pack of Card” technique is an appropriate option. The interviewer is guiding the interviewee while playing with the cards. If a group of experts from different companies gather to work together in one location, another input mechanism should be used. The interviewer has to be able to manually enter the data using a graphical interface or upload a simple formatted text file.

3.2 TOOL: Real-time Computing for Quicker Feedback and Re-evaluation Possibility

When the data collection process is finished, experts tend to ask for real-time feedback of their results. They are eager to know how they compare to the rest of the group. In order to satisfy their desire, the interviewer should be able to compute and aggregate the data directly. A quick feedback from the tool also allows experts to revise the data input if errors have been made. Having interactions between the interviewer and interviewee right after the data computation makes discussions about the results much richer.

Experts should be able to interpret the results obtained with the MCDM methods selected. These methods should be simple enough for experts to understand how results are related to the data collected. Moreover, the selected methods should allow a certain degree of aggregation as to enable a group MCDM model based on all individual models. Finally, if changes have to be made after computing the data, the tool should support data updates. A robustness analysis is also welcome in order to indicate to the experts which evaluation is more likely to be changed, either because of an error or a misunderstanding.

3.2.1 Design Proposition IV: Combining Complementary MCDM Methods

In line with the problem at hand, we reviewed advantages and drawbacks of several MCDM methods. Our choice was based on two main constraints: (i) the data collection requirements (i.e., easy and fast) and (ii) computation algorithms (i.e., simple and understandable for participants). We selected ELECTRE I (Benayoun et al. 1966) and the weighted sum model (WSM) (Fishburn 1967), as the set of data required to run the computation of both methods is compatible. ELECTRE I comes from the family of the "outranking methods", while the WSM enables the computation of a ranking of the best alternatives based on the preferences collected. The computation of both methods is simple enough for the experts to understand how results are obtained.

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. In other words, ELECTRE I reveals the ideal alternatives with a maximum of advantages and a minimum of inconveniences in the function of various criteria.

To present the algorithm used for ELECTRE I, we propose a pair of alternatives "a" and "b". Each criterion is assigned a weight w_j (j = 1, n; n = number of criteria). The *concordance index* is defined as follows:

$$c_{a,b} = \frac{1}{W} \sum_{\forall j:\, g_j(a) \geq g_j(b)} w_j \tag{1}$$

where $W = \sum_{j=1}^{n} w_j$ and $g_j(a)$ is the score for technology a under criterion j.

The *discordance index* is defined as follows:

$$d_{a,b} = 0 \quad \text{if } g_j(a) \geq g_j(b) \ \forall j \tag{2}$$

Otherwise,

$$d_{a,b} = \max_j \left[\frac{g_j(b) - g_j(a)}{\delta_j} \right] \tag{3}$$

where δ_j is the range of the scale associated with the criterion j.

Both index values are then compared with the respective threshold (s_c and s_d) to determine their significance. A concordance and discordance value are considered significant if

$$c_{a,b} \geq s_c$$
$$d_{a,b} < s_d$$

The outranking relation $r_{a,b}$ is defined as:

$$r_{a,b} = \begin{cases} 1 & \text{if } c_{a,b} \geq s_c \text{ and } d_{a,b} < s_d \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The result of ELECTRE I is an outranking graph or matrix which will display which alternative is significantly preferred over another one.

On the other side, the WSM produces a ranking of alternatives. The basic logic is to compute a weighted sum of the evaluations of each alternative over all criteria. The greater the weighted sum the more preferred the alternative (Fishburn 1967). The WSM score (S) for the alternatives (i) is defined as follows:

$$S_i = \sum_{j=1}^{n} e_{ij} w_j, \quad \text{for i} = 1, 2, 3, \ldots, \text{m}. \tag{5}$$

where e_{ij} is the evaluation of the alternative i for criterion j, and w_j is the weight of criterion j.

3.2.2 Design proposition V: Aggregation of Individual Results for Group Analysis

In order to identify a possible consensus between the experts, we suggest the addition of a group decision feature to our algorithm. Bui and Jarke (1984) have previously proposed a method based on ELECTRE I for group decision making. They suggested applying the min–max concept of game theory (Neumann and Morgenstern 1953). To reach a consensus, this method takes the most severe technology evaluations for each criteria done by any actor (n is the number of actors). The group concordance ($c^G_{a,b}$) and discordance ($d^G_{a,b}$) indices could be defined as:

$$c^G_{a,b} = \min \left[c_{a_u,b_u} \mid u = 1, \ldots, n \right] \tag{6}$$

$$d^G_{a,b} = \max \left[d_{a_u,b_u} \mid u = 1, \ldots, n \right] \tag{7}$$

and the group concordance (p^G) and discordance (q^G) thresholds can be respectively computed as follows:

$$p^G = \max \left[p_u \mid u = 1, \ldots, n \right] \tag{8}$$

$$q^G = \min \left[q_u \mid u = 1, \ldots, n \right] \tag{9}$$

where p_u is the concordance and q_u is the discordance thresholds for each actor u. For the WSM, we also added a group feature in the algorithm. The group score (G) for the alternative (i) is defined as follows:

$$G_i = \sum_{k=1}^{o} \sum_{j=1}^{n} e_{ijk} w_{jk}, \quad \text{for} i = 1, 2, 3, \ldots, m. \tag{10}$$

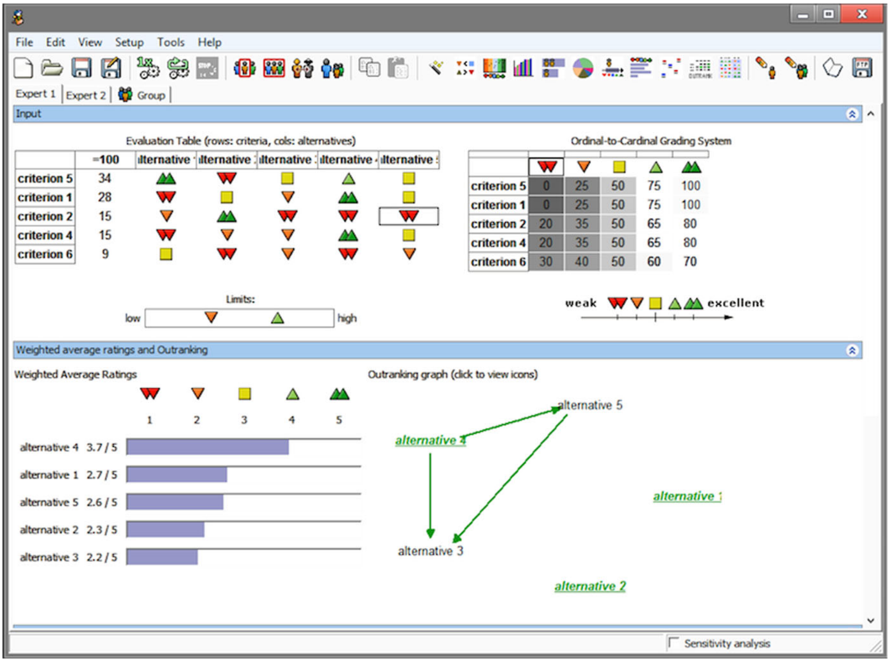


Fig. 3 An illustration of the mainscreen of the tool designed

where e_{ijk} is the evaluation of the alternative i for criterion j by the expert k, and w_jk is the weight of criterion j by expert k.

3.2.3 Design Proposition VI: Compute Data Realtime for Instant Feedback

As stated above, the tool should allow realtime computation in order to give quick feedback to the experts. After individual evaluations are added to the model, experts can revise their preferences if they feel that they made a mistake. Through the whole data collection and computation process, the data collector can interact with the experts to answer questions or concerns for instance. This feature aims at limiting the input of errors in the model. As opposed to other tools tested, the main screen displays both the data collected and the results at once (see Fig. 3). The tool computes 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 option enables a "what if" sensitivity analysis capability as by giving instantaneous feedback for any changes made in the data matrix. This module helps to evaluate the stability of the analysis and supports an exploration of alternative scenarios.

In some cases, an experts hesitates about a particular evaluation. For instance, in Fig. 4, the expert evaluated the alternative 2 on criterion 2 as "excellent". If the expert hesitates with "good" or "average", the tool indicates that the change would not matter, as it would not have an effect on the outranking relations. However, if the expert would like to change to "fair", then it will have an impact on the overall analysis. Computing

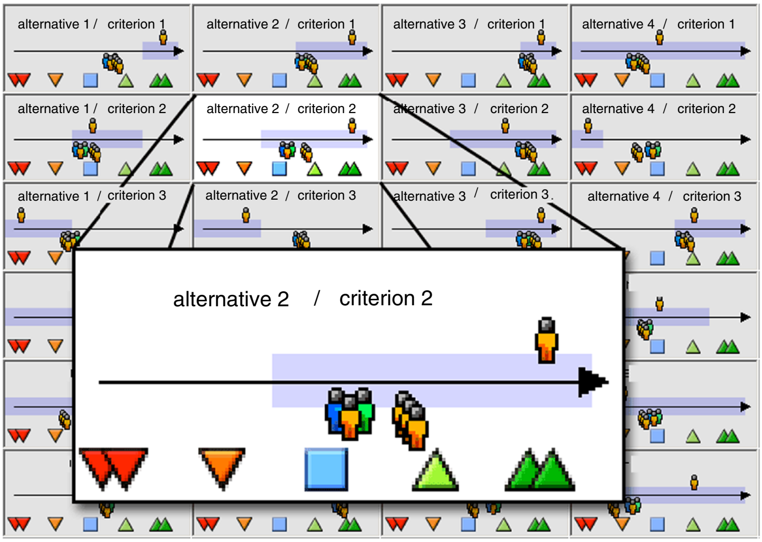


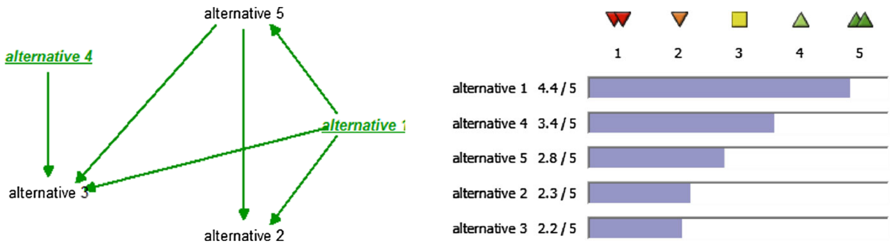
Fig. 4 Individual robustness analysis

the robustness of a single evaluation is quite practical when refining the analysis for a given expert.

The Individual Robustness Analysis automatically computes all of the limits (i.e., purple zone on the arrow) within which the experts can change evaluations without changing the overall result of the analysis. The matrix gives an instant overview of evaluations and their impact on the outcome. This matrix can help to compare the position of a selected actor with the average evaluation of the whole group and its family (if experts are grouped in industries for example). This module is helpful to detect evaluations that prevent a group consensus. Diverging evaluations could be opposed opinions, errors, or simply a demonstration of knowledge disparities between the experts. Sometimes, experts are just more knowledgable about certain alternatives than others.

3.3 OUTPUT: Improving Visualization of Data and Results to Facilitate Identification of Possible Weak Signals

The output of MCDM methods is often represented in form of matrix or table. Visualization of the data collected and results is limited in most cases. A human intervention is required in order to draw or represent the data differently. If no specific visualization efforts are made, getting a quick feedback or overview of the data is challenging. Moreover, the use of a visualization tool would help unveiling patterns and consensus possibility, especially in presence of a large dataset. In technology foresight, the quality of the input as well as the clarity of the output are essential for unveiling trends. Having a colorful and highly-interactive user interface facilitates a more efficient and effective representation of the data and results. Moreover, the tool should be flexible enough to allow the creation and storage of different scenarios.



(a) **(b)**

Fig. 5 An illustration of the two different perspectives on the results. **a** ELECTRE I. **b** Weighted sum model

Our tool provides two main types of output. The tool displays the results of the MCDM models' computation. Moreover, various visualization modules are available to compare and scrutinize the data collected from different perspectives. We also implemented a scenario building feature in order to store different states of analysis.

3.3.1 Design Proposition VII: Support an Effective Visualization of the Results

The visualization of the results of MCDM methods comprises two perspectives: (i) outranking relations (ELECTRE I) and (ii) a ranking of alternatives (WSM). The complementarity of the two methods helps to visualize the outcome in two different manners. The graphical representations can be easily interpreted by experts.

The outranking relations of ELECTRE I 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 discordance threshold which can be seen as severity levels over and under which an action could outrank another. The results of ELECTRE 1 can be presented with a matrix containing "1s and 0s" to indicate which alternative outranks an other. Yet, a better way of visualizing these relations are outranking graphs as they are easily understandable. In Fig. 5a, alternative 1 outranks alternatives 2, 3 and 5 but not 4. It means that alternative 1 is significantly preferred to 2, 3 and 5 but we cannot compare it with alternative 4. Moreover, the alternatives that are not outranked belong to a core which regroups the best solutions. In our case, alternative 1 and 4 belong to this core. If an arrow is bi-directional, it just means that the two alternative are equivalent.

The results obtained with WSM are represented in a simple ranking which displays the score of each alternative (see Fig. 5b). The scale to calculate the scores is predefined as 1 for weak, 2 for fair, 3 for average, 4 for good, and 5 for excellent.

3.3.2 Design Proposition VIII: Support the Comparison of the Data and Results

Individual experts need to see their own results as well as how they compare to the group of experts. We developed a number of visualization modules to address this requirement. In this section, only three modules will be presented as space is limited. The first module gives a quick overview of all the evaluation of the group of experts.

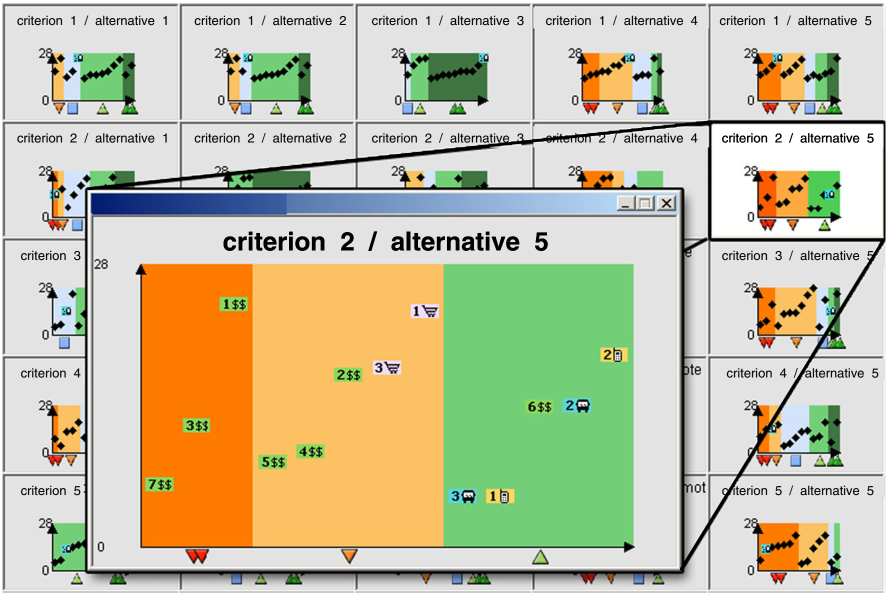


Fig. 6 Comparison of the evaluations and weights

The second module displays the weights given to the criteria by all the experts. The third module shows all the experts' evaluations for one selected alternative.

Figure 6 exhibits a quick overview of how much the experts agree on the evaluation of an alternative. All the evaluation of experts are displayed in one large matrix (background image). Details for each evaluation can be obtained by clicking one of the small graphs located in the matrix (here criterion 2 for alternative 5). The graphic is vertically sliced into zones devoted to the evaluation (scale). The height represents the weight for the criterion (i.e. the higher the position, the more important the criterion is for the expert). In other words, each small icon represents the evaluation and the weight of an actor. In this graph, an actor is defined by a number and its industry (different icon and color).

If the color of the graph is uniform, it means that the experts tend to agree. If the graph looks like a rainbow, it indicates that experts do not agree. The size of the colored zone is also important as it shows approximately the number of experts who have the same evaluation (not necessarily the same weight). A large green zone means that the experts evaluate the alternative as good or excellent for the given criterion. A red or orange zone stipulates that experts evaluate the alternative as weak or fair.

Figure 7 shows the individual weights of each expert for each criteria in a matrix. Again, by clicking on the matrix it is possible to zoom on one graph and obtain more details. This matrix is useful to rapidly observe if experts agree or disagree on the importance of criteria. An exponential curve shows that the experts do not have the same priority on the criterion. However, a flat horizontal line means that the criterion has the same importance for all the experts. An additional feature on this graph is the possibility to identify the family (industry) each experts belongs to. This helps

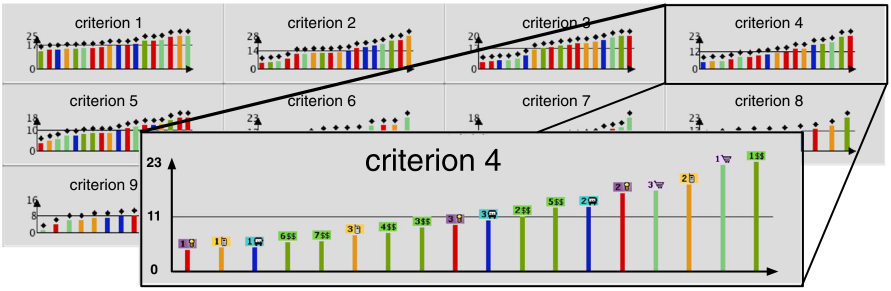


Fig. 7 Comparison of the weights

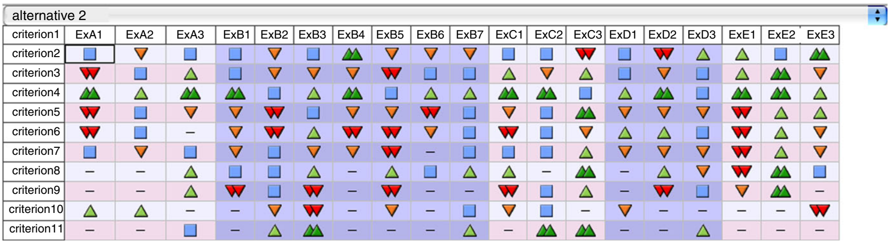


Fig. 8 Evaluations of a given alternative

to identify industry patterns for the importance of the criterion. In our example, we observe that expert do not really have the same priorities for criterion 4. The average weight is “11” (on a 100), while the maximum is “23” and minimum “5”. About half of the experts are below the average and about half above the average. In this particular graph, we do not really a pattern for experts coming from the same industry (family).

We built an additional matrix to get a more precise overview of all the evaluations done by the experts (Fig. 8). This matrix enables to quickly identify if the evaluations are good or bad for a given alternative, just by looking at the dominant colors. The experts are grouped by family (coloring of columns).

Other comparison modules have been developed. Each module has a precise objective. Either the module provides an overview to quickly identify a trend or allows a more detailed view, to obtain a precise comparison of selected experts, evaluations, or criteria.

3.3.3 Design Proposition IX: Allow the Creation and Storage of Alternative Scenarios

Another essential capability of our tool is the sensitivity analysis feature, which is impossible to obtain without the help of a dedicated computerized tool. The tool can simulate changes and indicate which expert, evaluation, or criterion could change the group consensus. For example, it is possible to simulate an improvement of alternative 1 in terms of criterion 2 and observe the changes in the model in a realtime manner. We could also insert new alternatives and observe the impacts in a given MCDM model. For each change made, our tool supports the storage and facilitates browsing in between models.

In order to conduct the foresight analysis, we first establish a model with current alternatives. This first model is used for assessment and benchmarking purposes. Then, we add a new (future) alternative into the model. The insertion on the additional alternative aims at observing the impacts generated within the first model. We assume that the experts do not change their evaluations about former alternatives. If the additional alternative performs better than the former alternatives, we could consider the additional alternative as a serious option for future developments.

4 Evaluation of the FSS and Our Design Propositions: Foresight of a Mobile Payment Situation

In this section, we describe the evaluation of our tool. This stage is considered to be central and essential for any design science research project (Gregor and Hevner 2013). The evaluation provides evidence that the designed tool "works" or achieves its purpose (March and Smith 1995; Venable et al. 2012). The overall utility, quality, and efficacy of the tool depends on various characteristics such as functionality, completeness, consistency, accuracy, performance, reliability, usability, and other relevant quality attributes (Hevner et al. 2004). The objective is not to check each factor one by one but select the aspects that are the most relevant to assess. Hevner et al. (2004) also propose different methods for evaluation: (i) observations (e.g., case and field studies), (ii) analyses (e.g., architecture, optimization), (iii) experiments (e.g., simulations), (iv) tests on the functions and structures, and (v) descriptions (e.g., informed arguments, scenarios). An evaluation can be a simple demonstration (light-weight evaluation that shows the utility of the tool at least in one context) or a more formal and extensive process with a positivistic stance using objective quantitative performance measures (Peffers et al. 2007). As a conclusion, Venable et al. (2012) explain that despite the wide number of evaluation methods available, there is little guidance in selecting the among methods and designing the right evaluation strategy.

To guide the evaluation of our tool ex post, we adopted a framework for design science research proposed by Venable et al. (2012). Their 2-by-2 framework implies that an evaluation can be done ex ante and ex post in either *naturalistic* (i.e., real people, real systems, real settings (Sun and Kantor 2006) or *artificial* environments. The use of the dimensions presented can be mixed as a design project has several "build and evaluate" iterations (March and Smith 1995). At the beginning of a design project, an ex ante evaluation with an artificial environment might be more appropriate while the final design tool (ex post) should be evaluated in a naturalistic environment to offer a better validity (Venable et al. 2012).

The tool has been developed through several iterations in order to comply with the specifications derived from our design propositions. As a result, we had several evaluations. During the first software development phases, we tested the tool in our laboratory with a fictitious set of data (i.e., ex ante, artificial). Once the tool was ready to be used in real settings, we proceeded with several "build and evaluate" loops (i.e., ex post, naturalistic). As we had a real problem to solve with real people, our primary objective was to evaluate the utility and effectiveness (i.e., works in real situation) of our tool to support and facilitate a technology foresight using MCDM methods. Other factors such as efficiency (minimizing resources) and representativity of the results were also part of the evaluation.

The main evaluation our designed tool (i.e., field study) took place in naturalistic settings with experts with a concrete problem at hand. The mobile payment market in Switzerland had adequate characteristics to be a good field for our evaluation. The developments of mobile payment have been slow for many years despite numerous optimistic predictions. The market is characterized by high uncertainty about emerging alternatives. Moreover, the market is subject to conflicting interests of experts working in different industries. To succeed in this field experiment, an essential requirement was the ability to gather an exhaustive set of representative experts from the different companies active in the market. Our objective was to use our designed tool in order to get a better understanding of the market and detect weak signals of possible technological and organizational evolutions.

In this evaluation section, we purposely do not emphasize on the actually analysis of collected and the results obtained during the field experiment. A more detailed analysis can be found in previously published studies which focus specifically on the mobile payment issues Ondrus and Pigneur (2007, 2009)

4.1 A Technology Foresight Exercise for the Swiss Mobile Payment Market

As we wanted to better grasp the problem of the Swiss market, we first examined other, more advanced markets to see what types of shift occurred. We looked into the Japanese and the Hong Kong markets and observed two shifts. In Japan, consumers could use their mobile phones to make proximity payments. In Hong Kong, the Mass Transit Railway Corporation (MTRC) has been able to launch a very successful scheme with Octopus. The lesson learned from the Hong Kong experience is that a self-organized scheme offered by an independent or a consortium of independents (e.g., public transportation companies, retailers) could enable a new industrial organization of the payment market. Based on the two cases, we identified two possible evolutions we wanted to study for the Swiss context.

4.1.1 Evolution I: Mobile Phone Payment Schemes Could Threaten the Established Payment Systems in Switzerland

The first potential evolution could a shift from card-based to phone-based solutions. Today, card-based payment schemes are widely accepted. However, with high market penetration of mobile phones and the digitalization of the payment process, phone-based solutions could become an inherent threat for current card-based schemes. We added money (i.e., cash) for benchmarking purposes. The technology alternatives and criteria used for this analysis are listed in Table 2.

Table 2 Technology-alternatives and criteria

Alternatives	List of criteria
Money—*benchmark*	Ease of use, cost, reliability, user/market acceptance, flexibility, value proposition improvement, maturity, speed, scalability
Magnetic card	
Smartcard	
Contactless card	
Mobile phone “remote”	
Mobile phone “proximity”	
NFC—*foresight*	

Table 3 Organization-alternatives and criteria

Alternatives	List of criteria
Independent solution	Cost, CRM, differentiation, flexibility, interoperability risk, scale, security
Consortium solution	
Financial institutions solution	
Telcos solution	
Financial institutions and telcos solution	

4.1.2 Evolution II: Payment Systems Provided by Self-organized Actors Could Threaten the Ones Provided by Operators

The second evolution studied is organization-based (i.e. a switch from a dominant operator-driven to a more self-organized solution). Financial institutions and MNOs are dominant actors in the mobile payments market. However, merchants or newcomers could launch independent payment schemes that could compete with the current ones operated exclusively by financial institutions. We wanted to explore the different industry organizations that could emerge in the Swiss payment market (see Table 3).

The two lists of criteria was extracted from the literature, discussed in focus groups and validated with several experts. The preselection of criteria was done to facilitate the work of experts during the interviews. During data collection, each expert could still add or remove the criteria they considered relevant or irrelevant.

4.2 The Experiment Settings

To fully represent the Swiss mobile payment market, we focused on five industries (financial institutions, MNOs, retailers, public transportation companies, technology providers). The 21 companies selected were the major firms in the Swiss mobile payment market in 2006. Each company was represented by one to three experts. The participating experts were the decision-makers and architects of the future developments in the Swiss payment market. The group was as exhaustive as possible. We interviewed experts in face-to-face settings (in their premises) using our tool installed on a laptop. Due to time constraints, we had to meet some experts several times to collect the data for both analyses (i.e., technology and organizational). The interviews usually lasted between one and 2 h.

As we wanted to test our tool in different settings, we also organized a 2-h workshop with all the experts. The main objective was to evaluate an upcoming alternative [i.e., near field communication (NFC)]. The first part consisted of a presentation of the previous results (i.e., assessment and benchmark of current alternatives). Then, to evaluate NFC, we distributed individual paper forms for each expert. These forms were customized with the criteria previously selected by each expert. We collected the forms and started to manually enter the evaluations in our tool. After having inserted and computed the data, we immediately exposed the results to the experts. This particular setting created the opportunity to evaluate the ability of our proposed design to collect data, analyze, and discuss the results in a workshop setting gathering all the experts.

4.3 Evaluation: the Tool Facilitates the Experts' Preference Elicitation (INPUT)

Our tool clearly improved the data collection process. We were able quickly to collect data for as many experts as required for the analysis. The repetitive way of collecting data for MCDM methods is monotonous. Using the tool with the computerized "Pack of Card" technique ended in a much faster and less painful data collection. Expert liked the process as it was interactive and convivial. We conducted interviews over a 7-month period. Our tool handled well the ad hoc additions of new experts' preferences. Its scalability was tested with more than 20 companies. The navigation between the different companies' MCDM models did not cause any problem. Finally, we were able to test the flexibility of our tool in different settings. We managed to collect data for one expert, several experts from the same companies (one model) and experts from various companies at the same time (workshop). In any of the described scenario, the tool helped us to quickly enter efficiently the data into the tool. The evaluation points are summarized in Fig. 9.

4.4 Evaluation: the Tool Gives Quicker Result Feedback and Re-evaluation Possibility (TOOL)

Thanks to the nature of the data collected, we could compute data with two MCDM methods which both provide different outcome. In several cases, we found that combining the two methods helped us to better explain the overall results of one company or an industry. The group decision feature allowed us to better understand the preferences of an individual company, a particular industry, or the whole market. Another essential feature of the tool was the realtime computing. This feature gave instant feedback to experts on their results as well as allowed to conduct some sensitivity analysis for robustness testing of the results obtained. The evaluation points are summarized in Fig. 10.

The use of ELECTRE I is resulting in outranking graphs which sometimes do not give much information about which solution is preferred, especially if thresholds are

	INPUT - *Facilitating the experts' preference elicitation*
Multi-criteria	*Design Proposition I: Computerized tool for facilitating the data collection*
	✓ Faster data collection than manual cards (from 1h hour to 30 min in average) ✓ Gamification of the data collection process ✓ No need for back office data input
Multi-actor	*Design Proposition II: Support scalability to include as many experts as needed*
	✓ Support the systematic addition of individual companies into the MCDM model ✓ MCDM model could contain more than 20 companies ✓ Easy navigation between the companies' models
Multi-stage	*Design Proposition III: Allow flexibility to use in different settings*
	✓ Data collection in one-to-one interview mode (one expert by company) ✓ Data collection in one-to-several interview mode (several experts by company) ✓ Use of the tool during workshop with 17 companies (several experts of several companies)

Fig. 9 Evaluation of the tool in light of the "INPUT" design propositions

	TOOL - *Real-time computing for quicker result feedback and re-evaluation possibility*
Multi-criteria	*Design proposition IV: Combining complementary MCDM methods*
	✓ Use of same data set for producing outranking graph and ranking ✓ Two complementary perspectives to analyze results
Multi-actor	*Design proposition V: Aggregation of individual results for group analysis*
	✓ Successful addition of each individual results in group model ✓ The group extensions for ELECTRE I and WSM support non-/consensus discovery
Multi-stage	*Design proposition VI: Compute data realtime for instant feedback*
	✓ Computation of the data was done instantly after collection ✓ Able to compute data realtime if any change

Fig. 10 Evaluation of the tool in light of the "TOOL" design propositions

too severe. In few cases, there were few or no outranking relations displayed. Experts were frustrated by such outcome. They felt that the time they spent was useless. By combining ELECTRE I and WSM, we were assured that we could always provide and comment some results to experts.

The algorithm proposed by Bui and Jarke (1984) worked well in order to obtain a group outranking graph. The addition of new experts in the group model fitted well. However, this algorithm had limitations. The more companies we added, the more likely the group outranking graph would not give any outranking relations. This issue can easily be explained as there was not a clear consensus in the market. Thus, the value of the WSM method became clear. We could get a group ranking even if the companies did not have a consensus.

The realtime computing capability of our tool was appreciated by the experts. A discussion on the result was possible right after the data collection. This way we did not have to go back to the experts later. One face-to-face meeting was enough

	OUTPUT - Improving visualization of data and results to facilitate identification of possible weak signals
Multi-criteria	*Design proposition VII: Support an effective visualization of the results*
	✓ Automatic display of the outranking graph and ranking side-by-side ✓ Rapid look at the results for individual companies and the group
Multi-actor	*Design proposition VIII: Support the comparison of the data and results*
	✓ Graphical comparison of individual companies' data to unveil industry patterns ✓ Identification of the reasons of non-consensus
Multi-stage	*Design proposition IX: Allow the creation and storage of alternative scenarios*
	✓ Sensitivity analysis used to explore different scenarios ✓ Successful addition of an additional alternatives (NFC) and storage of new analysis scenarios

Fig. 11 Evaluation of the tool in light of the "OUTPUT" design propositions

to collect data and discuss results. Moreover, we could tweak the results by using sensitivity analysis when experts wanted to change or test their preferences.

4.5 Evaluation: the Tool Improves Visualization of Data and Results to Facilitate Identification of Possible Weak Signals (OUTPUT)

We clearly focused the design of our tool on visualization capabilities. The richness of the data collected could only be exploited with a highly interactive user interface. The more data we collected, the more the tool showed its power in terms of scalability. Several modules were only exploitable when we reached a significant number of companies. We found that a major drawback of most tools previously tested was the visualization of the results and data collected. Moreover, the tool had to support the addition of new alternatives, new actors, new criteria as well as a "What if" analysis feature. The validation points are summarized in Fig. 11.

The results obtained by the two MCDM methods were complementary, particularly when displayed side-by-side. Some existing tools we tested were able to compute several MCDM methods but had separate windows to display the results. Therefore, it was difficult to quickly compare the results obtained using several MCDM methods. Our tool quickly displayed the results, compared to other tools tested. It helped us to explain and analyze the results in an timely way.

Using the group decision feature, we were able to unveil interesting results that we would not have discovered without the help of the tool. During our field experiment, we examined the group outranking graph of the three national mobile network operators. The graph showed that telcos would significantly prefer the "F&T" alternative to "Telco" or "Financial" (Fig. 12). Experts working for the financial institutions had exactly the same preferences. As these two groups of experts seem to agree that collaboration between them is the preferred alternative, it meant that both groups of experts were more likely to collaborate instead of competing.

As for the foresight, the creation of a future scenario with NFC was successful. We added the "NFC" alternative into the model and asked the experts to evaluate it. The

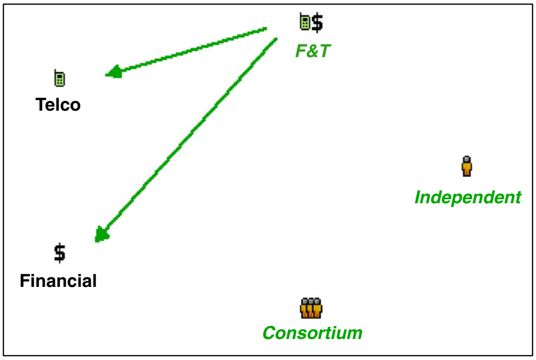


Fig. 12 Group outranking graph of the three MNOs–organization

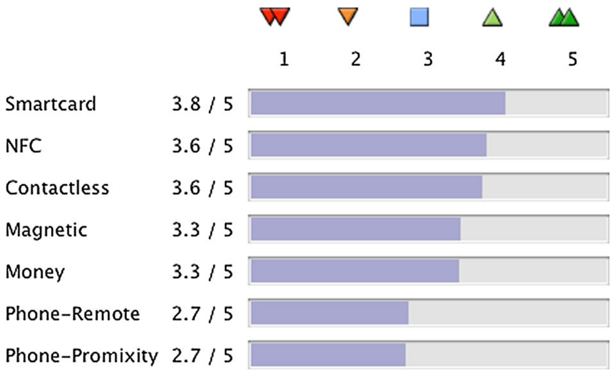


Fig. 13 Overall performance of NFC

results showed that it performed well (see Fig. 13). It was an interesting discovery as other mobile phone technology alternatives were underperforming in the previous model. This result indicated that NFC could be a reasonably good future alternative for setting up mobile payment systems.

4.6 Evaluation: Feedback from the Experts

In order to evaluate the utility and representability of our results, we interrogated the experts during and after the research project. We collected both qualitative quotes and quantitative evaluations of the results we obtained (Fig. 14). One expert expressed his appreciation for the realistic conclusions we obtained: "One of the rare pieces of research that represents well the current market". Another expert commented the results about his company: "Other companies like to work with us as we are more flexible than our competitors. The model depicts this situation very well". Another expert concluded that: "It is interesting that the results show precisely the disagreements which hindered the development of mobile payments in Switzerland". Overall, we got positive feedback from all the experts we re-contacted after the project. Moreover, the roundtable we organized with most of the experts provided additional validation of

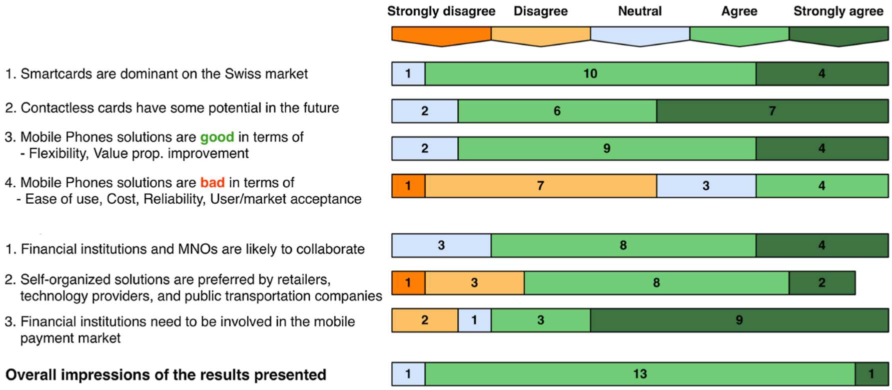


Fig. 14 Feedback given by the experts

the results with the survey. As can be seen in Fig. 14, the experts mostly agreed with our results.

5 Conclusion

In this paper, we presented a foresight approach using MCDM methods supported with a computerized tool (FSS). This FSS has been developed according to nine design propositions in order to enhance technology foresight processes and results. Not only the tool solved inherent problems of a foresight exercise but also demonstrated the relevance of adopting MCDM methods for such activity. A foresight process requires to establish the current situation, identify issues, include relevant stakeholders, and consider various perspectives. Our MCDM approach demonstrated that all these requirements were addressed.

This design science research project comes with a number of limitations. First, we used two classic MCDM methods for our tool. We did not develop any new algorithms that could have been more customized for technology forecasting. Consequently, our theoretical contribution is mainly on the original use of MCDM methods and not in the novelty of the methods themselves. Second, we did not try to compare our integrated and computerized approach with others technology forecasting methods. The objective was to design a new tool using MCDM methods that would help to better understand the mobile payment markets using multiple perspectives in a multi-actor context. Third, at this stage, we can only measure the success of our tool as a feasibility test of the use of MCDM methods for technology forecasting. Fourth, the tool was develop and use by us exclusively during the research project. Therefore, we did not make any usability tests that would conclude that the tool is appropriate for other users. We paid special attention on the readability of the results by the experts but not on the ease of use of the user interface. Finally, this project was specifically tailored to assess a market such as the mobile payment market. As our design iterations (i.e., build-and-evaluate loops) were highly influenced by the context studied, it is difficult to evaluate how appropriate the tool would be for other situations.

Despite the limitations, one essential contribution in this paper lies in the use of MCDM methods, not for decision-making, but for technology assessment and foresight. The use of MCDM methods for technology foresight has been suggested by Salo et al. (2003), but has not been fully explored in a real environment. Therefore, this paper contributes to the technology foresight body of knowledge by providing the design of an original multi-actor multi-criteria approach with an integrated tool.

In terms of the MCDM literature, we also demonstrated the use of different sets of criteria for each expert. In our case, we involved experts working for different industries with varying priorities. Each expert had the possibility to use a different set of criteria to evaluate the same alternatives. Usually, a group of decision-makers use the same criteria to evaluate the same alternatives. In terms of visualization, we explored the benefits of comparing side-by-side results obtained by two complementary MCDM methods in realtime.

As for the managerial implications, there was a real field experiment covering a national market. The foresight exercise on mobile payments in Switzerland involved experts from more than 20 companies. These experts represented the group of architects building the future of mobile payments in Switzerland. The results obtained with the FSS allowed to confirm the current status of the market as well as unveil possible future evolutions. Moreover, the granularity of the analysis was high enough to reveal the reasons why mobile phones were still not supported by most experts, especially from the financial industry. It also showed that Telcos should not develop a mobile payment solution by themselves (i.e., a trend observed on the market). Our research outcome generated positive feedback from the experts and the mobile payment community.

The next step of this research would be to use the tool in other context and see if the evaluation is comparable to the one presented in this paper. Another possible research is to benchmark the relative performance of our approach against other forecasting methods. New modern tools using different paradigms (e.g., prediction markets (Bruggen et al. 2010) are being deployed in corporate environments to enhance innovation (Rohrbeck and Gemunden 2011; Rohrbeck 2012).

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