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Sustainable R&D portfolio assessment

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Abstract

Research and development portfolio management is traditionally technologically and financially dominated, with little or no attention to the sustainable focus, which represents the triple bottom line: not only financial (and technical) issues but also human and environmental values. This is mainly due to the lack of quantified and reliable data on the human aspects of product/service development: usability, ecology, ethics, product experience, perceived quality etc. Even if these data are available, then consistent decision support tools are not ready available. Based on the findings from an industry review, we developed a DEA model that permits to support strategic R&D portfolio management. We underscore the usability of this approach with real life examples from two different industries: consumables and materials manufacturing (polymers).

Keywords: *R&D portfolio management, Data Envelopment Analysis, Sustainable R&D*

1. Introduction

1.1 Description of the problem context

Today's innovation strength is more than ever determined by a company's ability to differentiate from the competition in delivering customer delight at the pace of the market, applying the best available technology. Sustainable innovation results in profitable, people oriented, and planet-minded products and services. It is a great challenge for innovation and R&D managers to permanently assure that R&D budgets are allocated to the best set of R&D projects in order to reach the innovation targets on both the shorter and the longer term (Cooper [10], Cooper et al. [11]). Factors with a traditionally strong influence on strategic innovation decision making, such as the business opportunity and the feasibility of a project, do not necessarily predict project success (Moenaert et al. [24]). From their study, competitiveness reveals to be a strong predictor for success. Competitiveness consists of the following three elements: a competitive answer to a threat or an opportunity, the size of the advantage over the competition (incremental or game changing) and the sustainability of the innovation.

Competitiveness is linked with differentiation and added value as perceived by the customer. In order to create a sustainable advantage there is a need for non-imitable features, such as non-technological, intangible aspects leading to product/service experience and meaning, in line with the brand experience and corporate identity (Borja de Mozota [5]). This holds both for incremental as well as for radical innovations. However, the latter cannot be derived from actual user and market research, since they create new markets and envision the user of the future in a future context (Verganti [36]). Radical innovations, based on new technology, or addressing new user needs or creating new markets, are hard to evaluate, especially in the early phases of product development. There are many uncertainties and risks on all three types of innovation aspects: technology, economies and values, as shown in Figure 1. We define “Values” as the ethical, societal and personal values and perceptions leading to a product experience. Radical and incremental innovations differ dramatically in the availability of information on opportunities and risks. They are difficult to compare and equally serve the goals set by the business and innovation strategy. Industry practice shows that a separate approach in budget allocation and R&D organization for radical innovations is usually applied. This, however, does not solve the problem of evaluating the radical innovation projects. Optimal R&D budget allocation according to the innovation strategy requires incremental and radical innovations to be evaluated simultaneously.

Sustainability, as defined by the Brundtland Commission (UN documents [35]), was translated into the triple bottom line (people, planet, profit), and adopted by many companies through their mission statement and innovation strategy. However, the societal (people) and ecological (planet) dimension of sustainability are difficult to incorporate in formal decision making policies and decision support systems.

From a short term perspective, designing for user experience can lead to differentiation and innovation success and thus economic benefits. When embedded into a long term company strategy, aiming for “customer delight” involves human-centered design and experience innovation and leads to both incrementally and radically new products and services addressing today’s and tomorrow’s user needs. However, the economic benefits resulting from “user experience” are hard to estimate in the early phases of New Product Development (NPD). Moreover, the amount in which an innovation contributes to a user experience represents a completely different type of benefit for the company than the direct and short term economic consequences.

Ecology and human (or user) related aspects are part of the earlier defined as Values, since they both involve ethical values, which can be commonly shared by a group of customers or they can be individually perceived. Values cannot be translated into monetary figures without loss of information. They can be very different, even conflicting in their nature and value. For instance an innovation idea can lead to a very high user experience but low ecological contribution. They will therefore be treated as separate dimensions in the decision support for strategic innovation decisions.

R&D managers are in search of a consistent way to translate the innovation strategy into an R&D portfolio, taking into account all three dimensions of the sustainability concept. Available decision policies and supporting tools for strategic innovation decision making are not well capable of handling the intangible aspects of customer delight and ecology; they are too slow to respond to changes in both endogenous and exogenous factors. They favor incremental innovation versus radical innovations, especially when these originate from a user centered perspective.

As a result, mainly the technological and financial (market related) aspects prevail in the ranking and selection of projects at the strategic level, defining the R&D project portfolio. The disability to evaluate a projects’ performance level on the value-based aspects, and to evaluate its overall performance on technological, financial and value-based aspects forces ad hoc, subjective and informal decision making. This prevents a consistent value-based innovation strategy and R&D portfolio.

Innovation processes such as the widespread stage-gate® process, have many benefits for the management of risks and the monitoring of KPI's along the innovation funnel. However, the sequential process is not a reflection of the real-life, parallel and iterative innovation activity, and it has a tendency of favoring projects who are in their later phases of development (Repenning [28]).

Next to adequate decision support models and processes, the implementation of a sustainable R&D strategy requires a new mindset, reconciling an analytic as well as an intuitive approach (Martin [23]). Decision makers will face less certainty and will have to manage more risks and must be open to creative, intangible inputs during the R&D process. This will require a behavioral change in the decision making teams. In order to gain trust amongst the decision makers, it is of utmost importance to maintain transparency and consistency in the decision making, with a strong emphasis on communication based on the visualization of the data and results. This is a cornerstone of the "Design Thinking" way of R&D management, in which a holistic approach is applied and which applies rapid visualization of an idea and validation of each concept (Lockwood [22]). The decision support system we aim for should be capable to support Design Thinking on the strategic innovation level and therefore, besides transparency in the data, the system will have to possess quick recalculation functionalities and to provide an intuitive visualization of the model results.

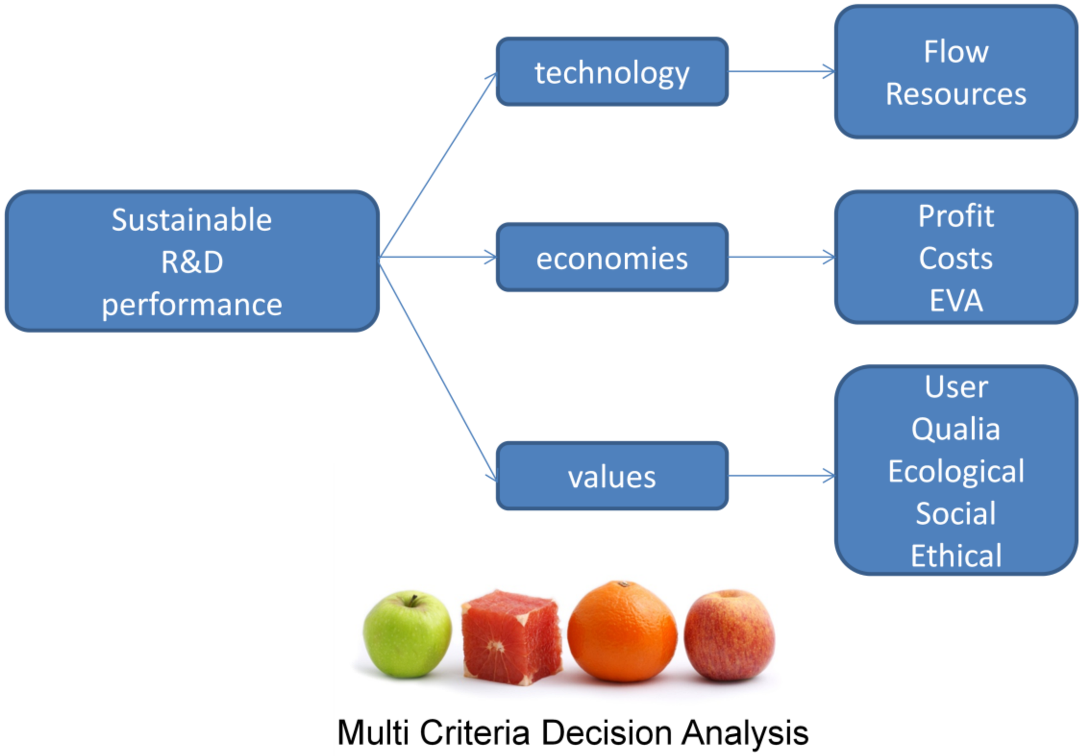


Figure 1. The multi criteria nature of R&D portfolio assessment.

Our approach is in line with findings in the literature. For instance (Brodt 2007), discusses the observation that product success is not only dependent on the technological and economical characteristics, but also relies on the experience of the product. The latter overlaps with our third cluster as depicted in Figure 1. Radical innovation design practice, based on product experience, has been developed by Hekkert et al. [16] through the ViP design methodology, in which user experience and contextual factors determine the innovation requirements. The corresponding dimensions are part of the "Values" in Figure 1.

1.2 Motivation: industry review

The first step in our research related to decision support for sustainability in R&D portfolio assessment, was a multilayered scan on how Flemish companies managed their R&D portfolio. Several ways were adopted to reveal the relevance of the business process named 'R&D portfolio management' whereof portfolio assessment is a crucial part. Our field research was structured as follows:

- Systematic audits and interviews at 100+ companies in Flanders across different sectors and ranging from SME's to large companies gave insights in the status of design management and R&D maturity. Most companies have a process and decision policies in place, but only very few realized the brand promise and company identity, including the values, in their innovation processes.

- Focus groups and discussion networks with industry captains (technology and plastics sector) were used to detect the future challenges regarding product portfolio, innovation and design management.

- In-depth interviews (25) with R&D managers and CEO's in the technology sector, incl. mechatronics and biotechnology, resulted in a detailed collection of data on innovation drivers, KPI's, portfolio management and decision processes, decision criteria, frequency of meetings, user involvement in R&D, R&D management responsibilities & constraints.

From this review, we were able to undoubtedly conclude on the real need for R&D assessment decision support in general and more specifically on the lack for a corresponding assessment model with the sustainability - and more broadly the value aspects - embedded in a decision support tool. It turned out that from a decision support point of view, the problem of R&D portfolio assessment encompasses:

- A low success ratio for **radical innovations** mainly due to failing **user acceptance,** and consequently a low ratio of radical innovation investments vs. investments incremental innovations.

- A **priority setting gap** between technology driven, and market driven R&D entities leading to **long decision cycles** and **inefficient R&D management**

- **Strategic directions** are directly labeled on individual projects in a straightforward way overruling the scoring models in place. These projects are hardly questioned during the course of R&D because they were imposed by another decision authority and are outside the formal decision process.

- **KPI**'s for R&D miss opportunity to drive improvement actions and target setting, because the link between these KPI's and the selection criteria is not always clear.

- **Sustainability** seems to be difficult to integrate in the formal decision process, it is either put forward as a strategic direction and is materialized in a few strategic projects, or it is found at the end of the development process where mainly incremental improvements can be expected.

- **Input data** based on human evaluations, used for score calculation, are not consistent. Sometimes different viewpoints, contexts or definitions are interpreted.

- R&D portfolio decisions are mainly made based on **economic figures**: NPV, ROI and other monetary metrics.

- **Intangibles** and **value-based arguments** are difficult to deal with for idea selection and project ranking and are not taken into account.

- Need for **dynamic** portfolio management tool allowing what-if analysis for changing external conditions with adequate frequency of updating.

- **Behavioral aspects** in decision making play an important role; shortcoming in visualization impedes good communication, the interpretation of the data differs between the members of the decision making group.

1.3 Industrial practice: R&D portfolio assessment tools

The industry review revealed several decision support tools in use today. Besides scoring models, the major characteristic of all these is that they are descriptive, leaving a huge opportunity for subjective inclusion of arguments and opinions. R&D managers state frequently that in this way consistency is hard to preserve whilst various stakeholders in the R&D assessment feel uncomfortable with the personal weight individuals can embed in the process. *"It is very difficult to objectively evaluate a promising technology driven research project, of which the economic value is based on estimations, against an incremental innovation project for a product segment in a prosperous market segment. Actual sales figures or a customer's request have more weight than a future potential."* The portfolio management goals, derived from the innovation strategy, can be diverse: to maximize project efficiency, to maintain a balanced portfolio or to aim for highest success ratio. They require different types of portfolio assessment tools and visualizations. As an illustration we list a few generic tools.

1.3.1 Bubble graphs, tables and spider graphs

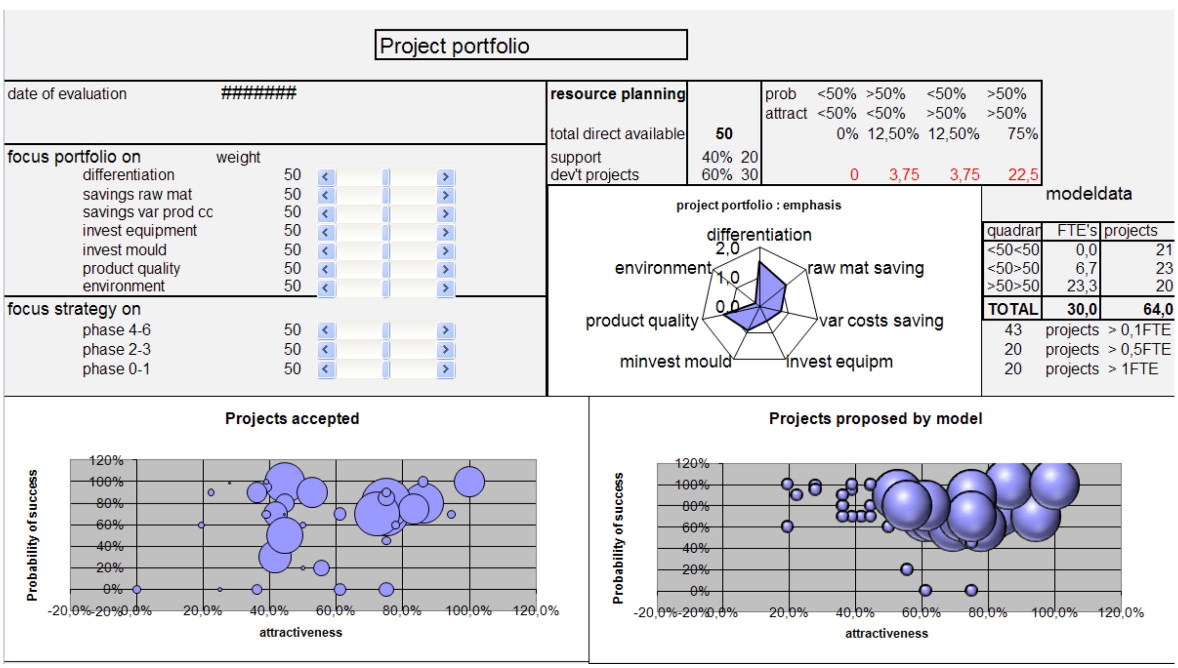


Figure 2. Portfolio dashboard

Bubble graphs (Fig 2.) are commonly used to visualize the results checklists or scoring models. Dimensions are typically consolidated units such as “opportunity/risk/resources needed” or detailed fragmented parameters such as “customer perception/technological risk/capital invested”. In each case the number of dimensions is limited to three, leaving the task of overall evaluation to the decision maker. A set of different bubble graphs are used in order to bring more clarity, but more often this leads to the opposite effect, due to the *bounded rationality* decision makers are subject to (Holt [17]). The graphs allow to define a “safe area” in which selected projects should be found, and they give a visual impression of balance on the dimensions chosen. As shown in Figure 2, it is possible to emphasize strategic choices by adapting the “portfolio focus” and process indicators with rules in the spreadsheet and thus putting more weight to the parameter. An immediate recalculation of the bubble graphs is then realized, which gives a potential for what-if analysis. The effect however, on the decision makers was confusion and lack of trust in the model. The data collection was a rigorous task, only performed once or twice a year.

1.3.2 Portfolio mapping – innovation level

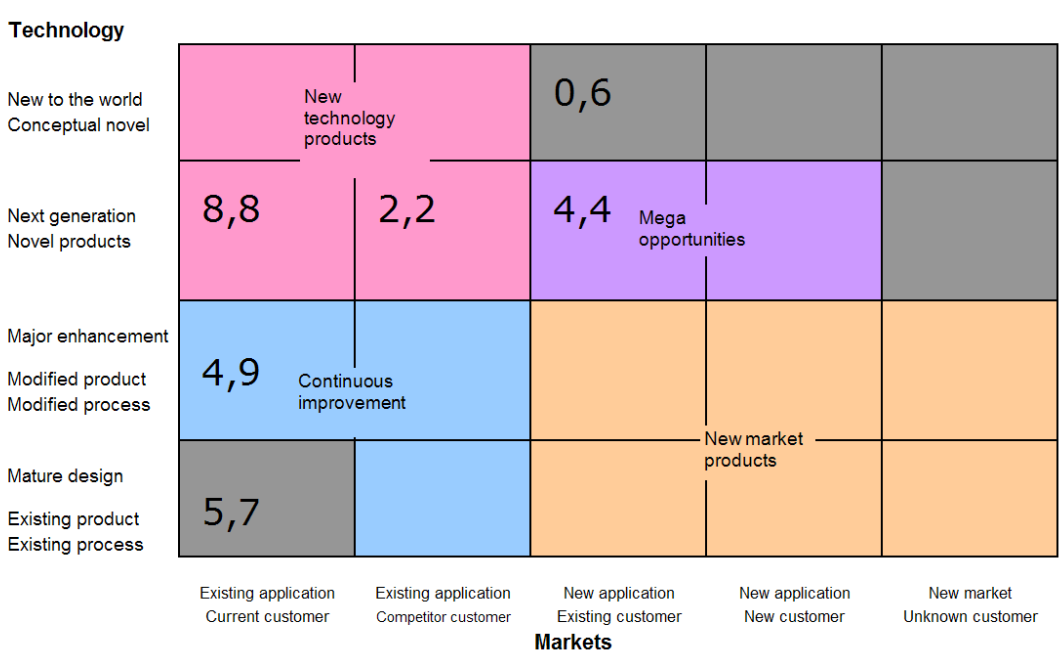


Figure 3. Portfolio mapping of innovation level

A two-dimensional mapping gives a view of the innovation ambition reflected in the portfolio. It is used as a 2^{nd} order mapping tool for balance in the portfolio, returning figures for KPI's and scorecards. It is usually updated once or twice a year.

Summarized, these tools have a low analytic content in the sense that they mainly try to map the data at hand. For the matter of decision support, they remain subject to personal opinions, power games, colored interpretations as well as they got stuck at only a partial analysis and thus limited view. However, our survey turned out that these decision support tools are quite popular and widespread. This is mainly due to two important features:

- The power of visualization. This is extremely important as these tools are used for group decision making. However, due to the 2/3 dimensional restriction these tools require oversimplification of the data or consolidation of different dimensions, which makes the result less transparent.

- The power of communication. This is a crucial step in order to disseminate the conclusions of the R&D assessment process.

As a consequence, these two observations put a necessary condition on the newly proposed decision support tool for R&D portfolio assessment.

2. Related academic work

The R&D portfolio management issue is moving away from the solely descriptive and graphical area as described in section 1.3 towards more systematic approaches (Kavadias and Chao [19]). Central is the issue of project ranking which has links with the allocation of budgets and resources (Cooper et al. [11]). Without going into detail, among the most popular ones are weighted scoring models, models which are based on a joint financial evaluation function or models which turn the diverse criteria into a single utility function. All these approaches are based on subjective weights related to the different criteria to aggregate the performance of the projects into one score for comparison. In this paper, we definitely want to go beyond this: the design of an assessment tool without predefined weights.

A consequence of a more systematic approach is that, when methodologies are used at regular intervals, the decision support tool can be employed for planning purposes. Formalisms like the Activity-Stage model (Baker [3]) and the Stage-Gate-model (Cooper [10]) are highly leveraged with a systematic underlying assessment methodology as described in this paper. In this way, the planning of R&D operations gets away from the power game image and will be less vulnerable to ad hoc circumstances.

The wide area of Analytic Hierarchy Process (Saaty [29]) is of course suitable for ranking and assessment. Calantone et al. [6], Poh et al. [25] and Ayag and Ozdemir [2] are examples where AHP is used to rank R&D projects. Ayag and Ozdemir [2] use a generalized version of AHP, namely Analytic Network Process (ANP).

Related is the work of Wei and Chang [37] where fuzzy numbers are used as a basis for fuzzy multi-criteria group decision making. Also here, subjective estimates of the fuzzy data are key. Huang et al. [18] describe a fuzzy AHP approach whereas Zhu [39] phrases his work as Imprecise DEA (IDEA).

From industrial (consultancy) practice, some approaches are known. Balanced score cards and simulation (like Analytica®, Enrich Consulting [15]) are often cited by companies. Although they offer nice representation and communication tools, they do not support the decision process that much and they lack the inclusion of sustainability dimensions.

In this paper we opt to use Data Envelopment Analysis (DEA) as our basic assessment methodology. The literature specifically related to DEA is summarized in section 4.2.

3. Problem definition and research contribution: disconnected decision making

Based on the industry review conclusions from section 1.2 and the literature review delineated in section 2, our paper makes contribution along the following lines:

- We use an analytic model (DEA) to assess the R&D portfolio in a systematic and a structured way. The pitfalls and subjective nature of traditional multi-attribute scoring models is avoided as there is no need for pre-agreed weights to put all performance measures into one evaluation function. Provided a comprehensive and complete set of performance criteria for the R&D portfolio, DEA can provide a single assessment together with information for the selection process, for technology road map construction and for decision consistency through time and serve as a basis for planning. This appealing managerial interest arises from the fact that R&D portfolio's can be compared over time and projected progress or regress can be monitored, controlled and acted upon. The power of our approach for communication purposes can therefore hardly be understated.
- Both quantitative and qualitative assessment criteria can be included; this is very useful to model the more value based and sustainability criteria as mentioned in section 1.1. Here we conducted intensive field research to select and validate the appropriate assessment criteria as well as their numerical data aspects. This is a part often left aside in the literature. Nevertheless, in practice this is a crucial but yet difficult challenge.
- Besides the development of a DEA-based decision support model, we truly believe that with this paper also a major contribution lies in the field of R&D planning practice. The R&D portfolio model plays a key role in (1) as a *tactical* layer serving as the interconnection between the strategic R&D mission and the operational R&D decisions and in (2) the *consolidation* of both internal (managing a set of portfolio's within the same organization) and external assessments (the own portfolio with respect to industry state-of-the-art portfolio's or with respect to competitor portfolio's). For instance, internally the R&D portfolio of both incremental and radical innovations can be jointly analyzed with respect for the specific characteristics of both clusters; also the combined portfolio's of different divisions within the same organization can be assessed in order to manage (or to refute?) the strategic bucket approach, as can be seen in figure 4 (Kavadias et al. [19]). More oriented towards benchmarking, it might be appropriate to include -

provided availability of data- competitor's projects or industrial standards or specific R&D pathways from the industry.

- For this type of decision support, an easy accessible and understandable computer implementation is mandatory. As the tool will be used in different meeting settings (both executive and operational meetings) and the tool needs to feed several modes of communication (e.g. reports, presentations, visuals, etc.), the computerized system must be low-entry and self explanatory. Although we used Lingo for our research purposes, we have made a start of turning the mathematical formulations into an operational business application. The computerized tool itself is not part of this paper.
- A final contribution of our research conveys several behavioral aspects of the R&D portfolio assessment process. This process can be highly sensitive as it may be subject to managers' beliefs and convictions, power games and communication skills of the individuals involved. Through our case based research approach, we experienced that the decision support system described in this paper to a great extent can help to 'de-mystiphicate' the R&D portfolio assessment process and bring it more towards transparent and consistent grounds. In this way, it enhances the very important strategic decision process of R&D portfolio management and provides a tool for *Design Thinking* in the company. This could eventually lead to better adapted organizations for radical, sustainable innovations.

As a matter of summary, we conclude this section with the phrasing of our research questions:

- Can we integrate sustainability in particular or value based criteria in general into R&D portfolio decision making?
- Can we make use of mathematical optimization (DEA) to support sustainable R&D portfolio management in a more complete, transparent and consistent way?

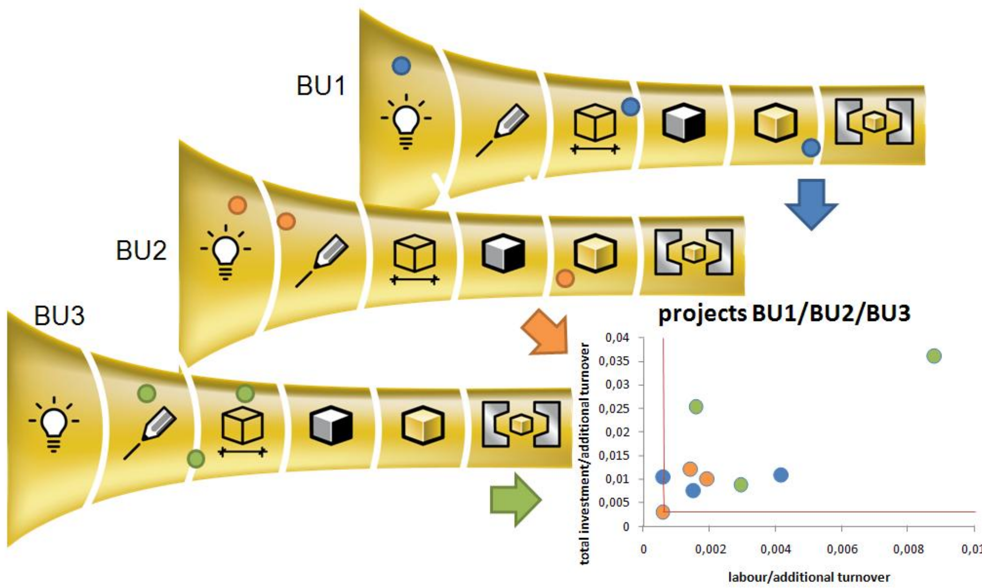


Figure 4. DEA allows consolidated portfolios

4. Methodology: case based research supported by quantitative analysis (DEA)

4.1Case based research

Based on the multi-layered scan of Flemish industry, we decided to opt for two typical case studies out of the set of companies reviewed as described in section 1.2 to test and validate our approach. They have been selected based on the their urgent need for scientifically based decision support in the area of R&D portfolio assessment, their reasonable availability of suitable data and a willingness to dive into a case based research path and to go along with the suggested mathematical modeling. In Figure 5, we list (part of) the information from the industry survey. The companies are clustered according their position in the value chain, based on the observation that the inclusion of the user/value dimension is one of the key determinants for successfully integrating sustainability in the R&D portfolio. For this paper we selected two cases along this axis: one global company active in the B2B material research area and another more local company active in the B2C end-product mass market. Both have expressed substantial interest in the decision support model for R&D portfolio assessment, but each one had its own specific emphasized interests related to sustainability:

- The B2B company is characterized by the additional challenging feature of consolidating the R&D portfolio's of several business units. Here the idea is neither to miss nor to overemphasize the sustainability issues over all existing and future business units.

- The B2C company faced a different challenge as the R&D portfolio is mixed up with incremental projects originating from both process and product improvement. Analogously, sustainability issues may be overwhelmed by incremental, and thus shorter term, concerns.

	B2B Material research	B2B Platform technology	B2B End product Professional market	B2C End product Mass market
Position in value chain				
Innovation drivers	1. technology 2. market (customers)	1. Technology 2. Market (customers)	1 Market (few customers)	1 Market (users & customers)
(end)User experience and interest	Sensory aspects: touch, visual, functional: weight, strength, cost	Functionality, cognitive & sensory	Functionality Multisensory	Multisensory Functionality
(end)User involvement in innovation	Scientific relation between multisensory experience and material properties	Indirectly Limited impact on decisions	Lead users From early stage of NPD	Market research: Usage and attitude studies User research for incremental innovation in later stages of NPD
strengths	Discovery of radically new possibilities from technology Awareness of ecology/trends/regulations	Technology driven radical innovations Ecodesign	Experience with lead user innovation	Experience with market and user research
weaknesses	Communication with future clients on user needs (incl qualia) and benefits from material properties	Add qualia to user needs and match with technical possibilities to beat competition Make better portfolio choices	Early detection of radically new technological opportunities relevant to future users	Early detection of radically new technological opportunities relevant to future users

Case 1 **Case 2**

Figure 5. Company categories based on the value chain position.

4.2 Multi dimensional approach: DEA

We opted to choose for DEA as the basic methodology to develop a decision support system for R&D portfolio assessment. Data Envelopment Analysis (DEA) is a generally accepted methodology for multi-attribute relative performance assessment (Charnes et al. [7]). For our purposes, where the units are the various projects to be assessed, it offers not only nice features for portfolio assessment and ranking, but it also turns out basic insights for portfolio selection, for portfolio management, the construction of technology roadmaps and even some possibilities for technology forecasting. In this paper we focus on the issues of assessment and ranking. From various sources in literature, we recall the following:

1. DEA is suitable for datasets with **heterogeneous dimensions;** as described in section 1, the overall assessment of a R&D portfolio boils down to technological, economical and value based performance measures, each stated in their respective measurement units. Note that value based performance measures may likely be expressed by scale or ordinal data; however, also some technological and economical measurements (e.g. risk assessment) may be described by ordinal data (Likert scales). For these data forms specific models have been developed (Cook et al. [9]).

2. Once the DEA model is agreed upon, it provides **rapid (re)calculation**. This is utmost welcome as several dimensions in the R&D portfolio assessment are volatile and subject to internal and external dynamics (for instance delivered test results, regulation changes, market/user reactions, competitive moves, ...). Also, as some of R&D measurements are based on opinions, expert knowledge, risk orientation and some kind of forecasting, rapid calculation is very useful to conduct what-if scenario's and sensitivity analysis. Rapid (re)calculation is also important if the methodology is used in a group decision making context, for instance in the format of the R&D portfolio meetings.

3. Provided appropriate choice of measurements and reliable data, DEA is able to give **insight** in the R&D portfolio. It points to (in)consistency in the data, it assesses the relevance of the measured dimensions, it may reveal clusters of projects and points to (in)balances in the R&D portfolio related to the overall risk content of the portfolio, the balance between radical and incremental projects, a shift in competitive position, etc.

4. By the adequate choice of performance criteria the DEA model can support both **strategy fulfilment** and **project performance**. In this way a connection is preserved with the strategic vision with respect to sustainability and emphasis of the company on the one hand, and tactical and operational

R&D management decisions on the other hand. As described in section 1.2, this is a major reason why current R&D portfolio assessment tools fail.

Several authors have tried to develop DEA models in the area of traditional project ranking and selection where they compare R&D departments, see Trappey et al. [34]. Linton et al. [20] suggest to use DEA to split up the projects into three categories: accepted, rejected and to be investigated. Eilat et al. [14] combine DEA with the balanced score card idea, which is incorporated through additional constraints, for instance to model strategic buckets. However, the latter is not without pitfalls (Dyson et al. [13]). Finally, DEA has also been tried to be combined with Quality Function Deployment as described by Ramanathan and Yunfeng [27].

A separate part of the literature deals with the integration of DEA and AHP (Ramanathan [26]). Chiang and Che [8] state that AHP can be used to preset bounds on the DEA weights, which are the decision variables within DEA. Similarly, Seifert and Zhu [30] and Takamura and Tone [33] incorporate AHP weights directly into their DEA models. Others like Shang and Sueyoshi [31] and Yang and Chunwei [38] use AHP techniques to preprocess data to be fed into DEA models. In the end, AHP is always built upon subjective considerations, be it for the weights itself as well as for the constraints related to those weights.

As our major focus is a practical decision support system for sustainable R&D portfolio assessment, a key issue was how to incorporate the assessments of the performance measures which are only available in a scale or an ordinal format, which is often the way how data on value based performance dimensions are collected. We have evaluated five models in our analysis:

1. DEA1: DEA model with cardinal data
2. DEA2: DEA model with ordinal data
3. DEA3: DEA model with categorical data
4. DEA4: DEA model with ordinal data as discrete cardinal data
5. DEA5: DEA model with ordinal data as continuous cardinal data

For easiness of reading, we refer to the appendix for a list and a discussion related to the suitability of the different DEA models. It turns out that the model DEA5 with ordinal as continuous cardinal data is both practical and robust enough for our purposes. Of course, this conclusion is related to the two cases studied in our case based approach. We now turn to how the DEA5 model has served in our case based research approach.

5. Real life applications

Due to confidentiality reasons, neither the company details nor the portfolio data can be disclosed. However, we report on the outcome of the case based research trajectory. As far as the DEA model building is concerned, for case 2 we have evaluated all DEA models listed in the appendix and came to the conclusion that DEA5 is well suited for our purposes. Based on this, for case 1 we limited the analysis to DEA5 only.

5.1. Case 1: Material Manufacturer

This section describes a multi-national, B2B material manufacturer in the plastic and foam industry. The company employs a centralized R&D portfolio covering different business units, among which some are active in rather mature markets whereas others are active in growing markets. The portfolio reviews research projects for new materials, new applications and new markets. However, alongside the case based research path, it became clear that particular incremental innovation projects were ear-marked with a priority set by top management. In this way top management overruled somehow any assessment and ranking.

It is important to know that this company has developed and used an elaborated R&D portfolio management system in the past. Relevant for this paper, it is worth to mention some of the main characteristics:

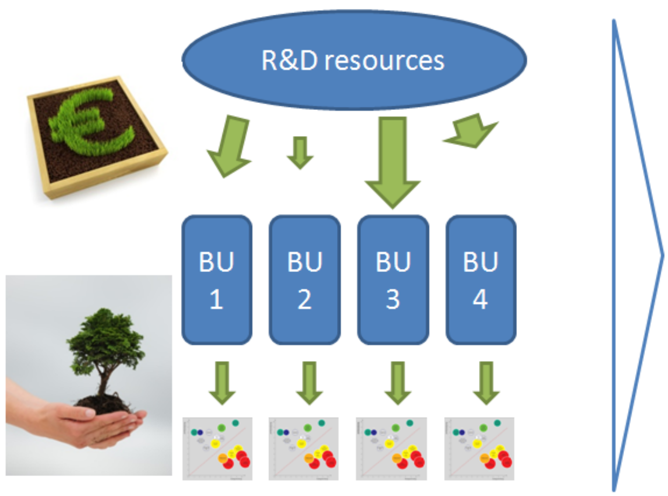
- it was based on a weighted scoring approach

- it was prone to manipulation: the different dimensions were given a weight which was utmost easy to adjust (see Figure 2, top left corner)
- the projects were visualized using radar graphs; these graphs do not only become pretty cumbersome with an increasing number of dimensions, but also lack the ability to rank the projects in a consistent and correct way
- visualization was always myopic: only three dimensions were visualized separately (the system consisted of several two-dimensional bubble graphs); in this way a holistic and complete view/assessment on the portfolio was never possible
- the system was based on many characteristics; there was no means available to limit the number of criteria (for instance if they were highly correlated); consequently, the amount of data to be collected was huge and envisioned resistance in many occasions

This elaborate R&D portfolio management system was abandoned due to its complexity and shrinking buy-in by the users of the system. In-transparency and blurred visualization added to this growing lack of interest.

Nevertheless, the company expressed its concern and belief that trends like sustainability in general and ecology in particular have to be incorporated in the R&D portfolio management agenda. Related to this is a growing concern about user perception of the companies' chemical and potentially hazardous reputation. On the other hand, the unique user experience potential, due to new material properties give rise to numerous new applications, which seem promising for those involved in R&D. However, the potential is difficult to put in numbers in the early stages of product development and the actual decision support is not able to reflect this potential.

With the available data we performed several DEA analyses which gave insight in the performance of the various innovation project types. It became clear that estimated parameters, such as "environmental strength", should be evaluated as fine as possible in order to return discriminating results. Even if the data are rough estimations, every difference between projects is valuable information. The fact that the data can be easily updated and the model can be re-run when new information gets available, lowers the anxiousness for early phase estimations. Due to the large amount of projects in the portfolio, we were able to work with 4 inputs and 8 output variables (**Fig. 4**), which included the full pallet of sustainable R&D portfolio: economic, technical and value aspects. Some left out variables will need to be measured or estimated in a more detailed way than the currently used 3- and 5-point Likert scales, other parameters did not justify further investigation, because they contained no new information or they revealed not to contribute to the ranking of the projects. Overall, the amount of work for data collection and data processing will be significantly reduced for a far better result. A challenge is here how to create room in the R&D environment in order to develop new businesses, from the research projects which have no proven market success yet but have a future potential due to value based aspects. This is done by adding criteria which are able to reflect the future potential based on the value aspects.



Inputs	Outputs
1. Development costs	1. Market size & growth
2. Investment costs	2. Competition
3. Technical risk	3. Sales potential
4. Commercial risk	4. Profitability
	5. Innovative step
	6. Trend strength
	7. Market position
	8. Environmental strength

Figure 6. DEA application in the B2B case

5.2. Case 2: Consumer Product Manufacturer

The company used a quantitative scoring model and a qualitative checklist. The scoring model was based on both calculations and human estimations. However, they were mainly economically driven.

The checklist provides detailed project information on all sustainability dimensions, in total 28 parameters are estimated per project. The two datasets were not linked for portfolio assessment, only the inputs for the scoring model were used.

Sustainability and user experience are main focus areas in the company's strategy. User insights and user involvement are of very high quality in the company. On strategic level however, the new product ideas resulting from user insights and radically new co-developed concepts are not able to gain attention next to incremental business driven innovations. We noticed that reactive projects, responding to a change in competitive environment, were systematically earmarked as "strategic", overruling the scoring model and the checklists. The company's mission and innovation strategy was to be a leader, but the portfolio was constructed for a follower. The aspect of ecology was considered as very important, but was not reflected in the decision support. This is a criterion which will be captured in the future to include in the DEA analysis. DEA analysis revealed a potential for reducing data collection of double measured, overlapping and inconsistent parameters and posed the right questions about the strategically earmarked projects (see Fig. 5). The 5-point Likert scale which was applied for many qualitative parameters will be refined and less parameters will be used. A summary of the different DEA analysis results can be found in Appendix 1.

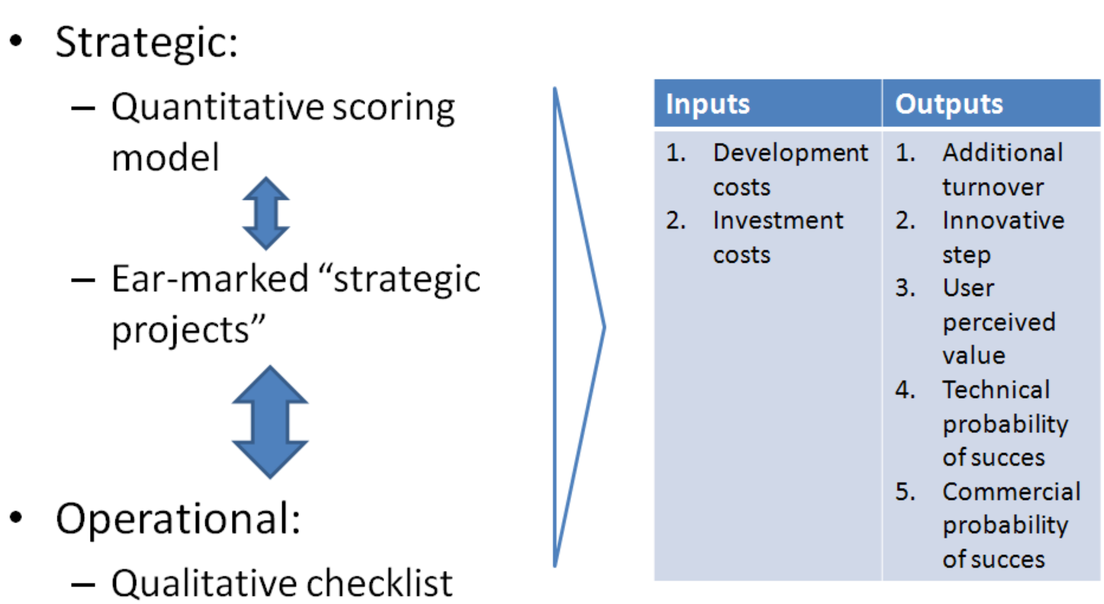


Figure 7. Case B2C company

6 . Management take-aways from case based research

Several take-aways can be distilled from the previous analysis:

- Immediate improvement actions for **data quality** and **efficiency of data** collection, creating stronger buy-in by all those involved
- Potential for **consolidated portfolio ranking & visualization**, revisiting strategic buckets
- Translation of **innovation strategy** into reliable criteria and KPI’s rather than specific projects
- From a behavioral point of view**, reactive** projects are usually positively influenced versus proactive ones, DEA can neutralize this
- Need for **clustering** of innovation types
- 2D views from the multidimensional analysis, give insight in improvement potential & explain (or question) earlier decisions

7. Concluding remarks

As a matter of conclusion, we revisit our research questions phrased earlier:

- Can we integrate sustainability in particular or value based criteria in general into R&D portfolio decision making?

As sustainability gets mixed with the other performance criteria, it imposes challenges on both the methodological and the practical side. From a methodological point of view, many of the value based criteria are descriptive and qualitative. Turning them into numbers is not trivial. Likert scales and categories have shown not to be that promising whilst the additional insight and value of these complicated models is questionable. Therefore, based on the two case studies revealed in this paper, we suggest to model the value based criteria as much as possible as continuous cardinal criteria. From the practical point of view, establishing good continuous cardinal measures for value based criteria is not obvious. The quest for good metrics, which are in line with the strategic mission and options, must be intensified and appropriate data collection processes have to set up. As far as the output from the decision support system is concerned, the visualization of the results turned out to be a key success factor. This is the solid base for proper and profound insight creation which serves on its turn as the fundament for clear and concise communication. As the R&D portfolio assessment process is a typical group decision exercise, the decision support tool has to fit this setting.

- Can we make use of mathematical optimization (DEA) to support sustainable R&D portfolio management in a more complete, transparent and consistent way?

Data Envelopment Analysis turned out to be a suitable methodology for R&D portfolio assessment, including the value based criteria. The main advantages are the fact that is complete (it summarizes the multiple criteria into one assessment and ranking), transparent (the assessment results can be justified and explained) and consistent (the methodology neutralizes subjectivity and circumstances). In a group decision process, it definitely takes care of the analytic part of the R&D portfolio game. Based on this analytic part, all other considerations can be added in order to come to a solid, well-thought decision. When this is done on a regular basis, opportunities in the field of R&D planning arise: project selection, ranking and clustering, resource allocation, R&D technology forecast, R&D road map construction, etc.

As far as future research is concerned we mainly believe that extensions on the proposed R&D portfolio assessment approach are to be formulated in the direction of project selection under constraints, the formulation of roadmaps for individual projects and the entire portfolio and to exploit the possibilities for portfolio follow-up and control.

Appendix

In our case based research path, we selected five models which looked promising in order to support our R&D portfolio management decision process and were able to include the sustainability aspect. First we review the five models. In the next section we summarize our findings from one of the cases conducted.

I. <u>Models used in the case based research path.</u>

The five models used in our analysis:

1. DEA1: DEA model with cardinal data

From the basic DEA models, we have the following categories:

   a. Constant Returns to Scale, versus Variable Returns to Scale
   b. Input oriented versus output oriented
   c. Radial (fixed mix of inputs and outputs:) versus Non-radial models (flexible mix of inputs and outputs:

We have chosen to use both the model of Charnes, Cooper and Rhodes [7], named CCR, which in our case is CRS, input oriented and radial. The model of Banker, Charnes and Cooper [4], named BCC, which in our case is VRS, input oriented and radial.

We rely on the following notation:

- θ is the radial measure for efficiency
- n is the number of DMU's under consideration (here the projects)
- m is the number of input variables
- d is the number of output variables
- x is the vector of m input variables
- y is the vector of d output variables
- The subscript o stands for the DMU under consideration
- X is a (m * n) matrix
- Y is a (d * n) matrix
- $\lambda = (\lambda_1, \dots, \lambda_n)^T$ is a non-negative vector

Then the decision model for DMU o is as follows:

$$\min \theta$$

$$st$$

$$\theta x_o - X\lambda \geq 0 \qquad (1)$$

$$Y\lambda \geq y_o \qquad (2)$$

$$\lambda \geq 0 \qquad (3)$$

This model produces a feasible solution the DMU under consideration if $\theta = 1, \lambda_o = 1, \lambda_j = 0\ (j \neq o)$. The optimal value for θ, noted as θ^*, is not larger than 1. Because $y_o \geq 0$ and $y_o \neq 0$, constraint (2) preserves the vector λ to be non-zero. This observation together with (1) leads to $0 < \theta^* \leq 1$. The model turns out an (input)vector x_o in order to obtain a smallest possible vector θx_o, whilst the output y_o is preserved. If $\theta^* < 1$, then $(X\lambda, Y\lambda)$ presents a better performance than $(\theta x_o , y_o)$. As a consequence, for a non-efficient DMU, input surpluses and output shortages can be obtained: $s^- = \theta x_o - X\lambda$ and $s^+ = Y\lambda - y_o$. In this way, a non-efficient DMU can be formulated as a linear combination of both the inputs and the outputs of the efficient DMU's related to DMU o, named the reference set E_o: $x_o\theta^* - s^{-*} = \sum_{j\epsilon E_o} \lambda_j^* x_j$ for the input criteria and $y_o + s^{+*} = \sum_{j\epsilon E_o} \lambda_j^* y_j$ for the output criteria, where the asterisk as * refers to the optimal values (Cooper et al., [12]). The model of Banker, Charnes en Cooper (BCC) differs only by adding the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$. Therefore, the measure of efficiency of the BCC model cannot be smaller than the measure of the CCR model.

2. DEA2: DEA model with ordinal data

This model is an extension on the basic model and combines cardinal with ordinal but continuous criteria, for which the weights have to be set up front. This is a major drawback of the model. Note that discrete ordinal numbers (like e.g. Likert data) cannot be handled. The model used is CRS, input oriented and radial. For our case studies, we only expose the model for ordinal output criteria. The model is along the lines of Cook and Zhou [9] and is as follows:

We rely on the following additional notation:

- R_1 is the set of cardinal output criteria
- R_2 is the set of ordinal output criteria
- I_1 is the set cardinal input criteria
- $Y_j^1 = \left(y_{rj}^1\right)$ is the vector of cardinal output criteria $r \in R_1$ for DMU j
- $Y_j^2 = \left(y_{rj}^2\right)$ is the vector of ordinal output criteria $r \in R_2$ for DMU j
- convention for the Likert scale: $y_r^2(l+1) - y_r^2(l) \geq \varepsilon$ where $y_r^2(l)$ the value related to a score l on the Likert scale for output criterion $r \in R_2$
- $X_j^1 = \left(x_{ij}^1\right)$ is the vector of input criteria $i \in I_1$voor DMU j
- L is the number of positions on the Likert scale

- $\gamma_{rj}(l) = 1\ if$ DMU j has a score l on the Likert scale for output r, otherwise $= 0$
- $y_{rj}^2 = y_r^2(l_{rj}) = \sum_{l=1}^{L} y_r^2(l)\,\gamma_{rj}(l) \qquad r \in R_2$
- $\Gamma_{rj}(l) = \sum_{k=l}^{L} \gamma_{rj}(k) \qquad r \in R_2$
- $s_r^+\ and\ s_i^-$ are the slack related to the cardinal output and input criteria respectively $(r \in R_1,$ $i \in I_1)$
- α_{rl}^1 is the slack related to the ordinal output criteria $(r \in R_2)$
- ε is a parameter, strictly larger than zero but smaller than any positive number

$$min\ \theta - \varepsilon \sum_{r\in R_1} s_r^+ - \varepsilon \sum_{i\in I_1} s_i^- - \varepsilon^2 \sum_{r\in R_2} \sum_{l=1}^{L} \alpha_{rl}^1$$

$$st$$

$$\sum_{j=1}^{n} \lambda_j y_{rj}^1 - s_r^+ = y_{ro}^1, \qquad r \in R_1 \tag{4}$$

$$\theta x_{io}^1 - \sum_{j=1}^{n} \lambda_j x_{ij}^1 - s_i^- = 0, \quad i \in I_1 \tag{5}$$

$$\sum_{j=1}^{n} \lambda_j \Gamma_{rj}(l) - \alpha_{rl}^1 = \Gamma_{ro}(l), \quad r \in R_2, l = 1, \dots, L \tag{6}$$

$$\lambda_j, s_r^+, s_i^-, \alpha_{rl}^1 \geq 0 \tag{7}$$

Note that the slack variables are explicitly present in this model and the parameter ε can be understood as the weight for slack variables in the efficiency of the DMU. Also an additional (non-linear) term ε^2 is added to the objective function. Constraint (6) is analogue to constraint (4): the model tries to find minimal input given equal output.

3. DEA3: DEA model with categorical data

For this model we rely on Löber and Staat [21], where ordinal data are presented as categorical data. The outcome are rankings within the predefined categories. Many ordinal numbers will produce many categories, which is a disadvantage as the technique only compares within categories and does not allow a comparison of projects in between categories. As these categories have to be decided up front, the ordinal scales can be transformed into a limited number of categories which is prone to subjectivity. Additionally, as in our case, the categories are derived from the ordinal scales, they are hierarchical: a DMU can only to be compared with A DMU of the same or a lower hierarchical class. In order to allow a DMU only be compared to the ones within the same or between lower class DMU’s, there is a need to introduce c-1 dummy variables (f^2 and f^3 in our case as we have only three categories). We refer to Löber and Staat [21] for more details. The model for our purposes is as follows:

We add the following notation:

- c is the number of categories
- B is the number of dummy variables f
- x_{ij} is an input variable i for DMU j
- y_{rj} is an output variable r for DMU j
- $o_{bj}^{(C_b)} = f_{bj}^{(C_b)} * y_{rj}$ where y_{rj} is any numerical output variable

  for instance: $f^2 = f^3 = 1$ if DMU j fits category one, $f^2=0$ en $f^3=1$ if DMU j fits category two and $f^2 = f^3=0$ if DMU j fits category three.

Then

$$min\,\theta$$

$$st$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \quad r = 1, \dots, d \tag{8}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta\, x_{io}, \quad i = 1, \dots, m \tag{9}$$

$$\sum_{j=1}^{n} \lambda_j o_{bj}^{(C_b)} \geq o_{bo}^{(C_b)}, \quad b = 1, \dots, B; C_b = 1, \dots, c-1 \tag{10}$$

$$\lambda_j, x_{ij}, y_{rj} \geq 0, \quad j = 1, \dots, n$$

Constraints (8) and (9) are identical to constraints (1) and (2) of the DEA1 model. Constraint (10) is analogue to constraint (8) and enforces that a DMU can only face refenerce DMU’s from the same or a lower category. In this way, a full ranking of all DMU’s is lost.

4. DEA4: DEA model with ordinal data as discrete cardinal data

Here we make the assumption that ordinal data can be mapped onto a discrete cardinal scale. This is often done when ‘verbal’ scales are turned into numerical scales. Although this approximation looks rough, it may turn out to be useful and suitable for practical purposes. The Full Disposal Hull (FDH) as described by Cooper et al. [12] is a suitable model for this. It is CRS, input oriented and radial. For matter of completeness, we mention the basic model hereafter:

$$min\ \theta$$

$$st$$

$$\theta x_o - X\lambda \geq 0 \tag{11}$$

$$Y\lambda \geq y_o \tag{12}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{13}$$

$$\lambda \in \{0,1\} \tag{14}$$

The additional constraints are (13) and (14). In this model, the efficiency of a DMU is only based on the performance of one and only one other DMU. As a consequence, the values for the ordinal variables can be outside the employed Likert scales. Also the discriminative power of the method is weak (Cooper et al., [12]).

5. DEA5: DEA model with ordinal data as continuous cardinal data

This is the same is model DEA1 but all ordinal criteria are handled just as they were continuous cardinal criteria. The model we evaluated is named Slack Based Measure (SBM) as described by Sueyoshi and Sekitani [32]). The SBM model uses a strong measure for efficiency, namely the Pareto-Koopmans efficiency, which equals the product of the radial CCR efficiency and the non-radial mix-efficiency of the DMU (Cooper at al., [12]). The model used is CRS and radial. However, due to its nature, it is neither input oriented nor output oriented:

With

- $s_r^+ \ and \ s_i^-$ as slack on the cardinal output and input criteria respectively
- t is a positive scalar
- $s_i^- = S_i^-/t^*, s_r^+ = S_r^+/t^*$
- $S^- = (S_1^-, \dots, S_m^-)^T$
- $S^+ = (S_1^+, \dots, S_d^+)^T$
- $\lambda^* = \Lambda^*/t^*$

$$min\ t - \frac{1}{m}\sum_{i=1}^{m} S_i^-/x_{io}$$

$$st$$

$$1 = t + \frac{1}{d}\sum_{r=1}^{d} S_r^+/y_{ro} \quad (15)$$

$$tx_o = X\Lambda + S^- \quad (16)$$

$$ty_o = Y\Lambda - S^+ \quad (17)$$

$$\Lambda \geq 0, S^- \geq 0, S^+ \geq 0, t > 0$$

Constraint (15) and the positive scalar t are the consequence of the linearization of the original problem. The constraints (16) and (17) are fixing the input surpluses and the output shortages. This means that the inefficiency can be split into the radial/weak inefficiency (like in the CCR model) on the one hand and the mix-inefficiency on the other hand.

II. Case based research findings

Given these five models, we summarize our findings here derived from our case based research. We report on the findings of the second case of the B2C company. For confidentiality reasons, we cannot expose the data, variables or other info. Be aware that this summary is put together at the end of the case based research quest, and that the final conclusions came through by repetitive proposition and refutation, the analysis of both input and output data and by rigorously employing the DEA models to underpin the R&D portfolio meetings:

- We observed the current practice of the company, which included a ranking based on personal judgement, scoring and discussion.
- The R&D portfolio contains 21 projects, data on several input and ouput characteristics were available. Some of the output characteristics which describe the sustainability issue were ordinal measurements (Likert scales 0-10).

- Top management earmarked three projects (projects 1,2 and 3) as strategically important. So they were ‘enforced’ to be high on the ranking and subsequent selection.

We structure our findings as follows:

- Correlation: Is the DEA ranking basically different from the current practice? We used the Spearman rank order correlation coefficient if applicable.
- Correlation+: Is the DEA ranking basically different from the current practice if the strategic projects 1, 2 and 3 are ranked first? We used the Spearman rank order correlation coefficient if applicable.
- # efficient: What is the number and the name of the efficient projects?
- Different: Which projects are clearly ranked differently compared to the current practice?
- Earmarked?: How many of the three strategically earmarked projects are ranked as efficient projects?

The results can be found in the following table:

	Correlation	Correlation+	# efficient	Different?	Earmarked?
DEA1	Sign. Pos.	Not sign.	BCC: 6 CCR: 6, 7, 8 , 10, 11, 13	9, 13, 16, 17, 21	0
DEA2	Sign. Pos.	Not sign.	6, 14, 17	17, 21	0
DEA3	-	-	11	-	0
DEA4	-	-	6	-	0
DEA5	Sign Pos.	Not sign.	6	8, 13, 20, 21	0

From the viewpoint of decision support we can conclude the following:

- Some models are able to grasp the implicit subjective partial rankings of the current practice. However, as soon as the strategically earmarked projects are introduced with their overruling ranks, the correlation is not significant.

- The number of efficient projects differs but project 6 looks like a generally agreed efficient project across the five models.
- Note that in none of the five models any of the strategically earmarked projects is efficient.

As a general conclusion from this case we took away that the DEA5 model behaves the best. Recall that is DEA5 the ordinal variables are treated as continuous cardinal variables. Bearing this in mind, the DEA5 model is reliable and useful in practice. For both cases reported in the main of the paper, we used DEA5. Similar conclusion has been obtained by Akyol and de Koster [1].

A final remark relates to the fact that senior management may want to overrule the ranking obtained by formal models. There are two options:

1. The strategic importance needs to be included in the model and as a consequence, a good metric has to be put forward.
2. Senior management has to justify the strategic overruling with additional, non-integrated arguments.

In both options it forces the R&D management team to go deep in the strategic importance of the projects, which is clearly received as an important asset of the R&D portfolio management decision support.

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