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Towards a Method to Improve Alignment of Objective and Subjective Information Requirements of Decision Makers – The Potential of System Dynamics for Information Requirement Analysis

by

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Towards a Method to Improve Alignment of Objective and Subjective Information Requirements of Decision Makers – The Potential of System Dynamics for Information Requirements Analysis

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Abstract

Despite valuable related work, identifying relevant information requirements of decision makers is still a key issue in developing analytical information systems. Since measures build a major basis for managerial decision making, discovering the objectively most important measures is crucial to reduce information overload and improve decision quality. Therefore, a method is proposed that helps decision makers to identify and to prioritize their measure-based information needs using the system dynamics methodology. As a result, objectively needed and subjectively believed to be needed information requirements are aligned. The applicability is exemplarily demonstrated using an existing system dynamics model.

1. Introduction

Supporting decision makers through adequate information supply has been an ongoing issue for both practitioners and academics for many years. But despite improvements triggered by scientific work, a recent IDC study reports that 75% of respondents still suffer from information overload [14]. Other studies indicate that about 50% of decision makers regularly face useless information [1, 10]. Typical results are unsatisfactory decision quality and a loss of productivity [4, 8]. Hence, there is a strong need to improve the information supply of decision makers with regards to selecting the right amount of the right information.

Analytical information systems nowadays form an essential part for information provisioning of decision makers. Although a standardized definition is difficult, they typically aim at supporting managerial decision making. One key peculiarity of building analytical information systems is the need to distinguish between informational and non-informational system requirements. The first are addressed by information requirements analysis (meaning the elicitation, documentation, and management of informational requirements) while the latter do not significantly differ from requirements of transaction-oriented information systems [28] and are therefore not considered in this paper.

As March and Hevner [16] point out, „IS professionals [have a] lack of adequate methodology to determine executive information needs" (p. 1035). [9] also identify the need for an improvement of analyzing capabilities – especially since careful a priori analyses of informational requirements constitute a success factor. In this paper, we examine the potential to use system dynamics (SD) as methodological basis to fill this gap. This approach seems promising since structural (cause-and-effect relationships) and behavioral (equation-based simulation) aspects can be combined. While other approaches are also able to comprehensively express causal relationships (as e.g. Balanced Scorecards or Strategy Maps [27]), they lack the quantitative ties between these relationships required to prioritize information needs. Approaches focusing e.g. on correlations [20] consider these ties but lack the causal connections between information structures. Hence, the possibility to combine qualitative descriptions with quantitative simulations is a vital advantage of SD.

To gain a shared conceptualization of information needs and related terms, we subsequently refer to the terminology introduced by [30] (see figure 1).

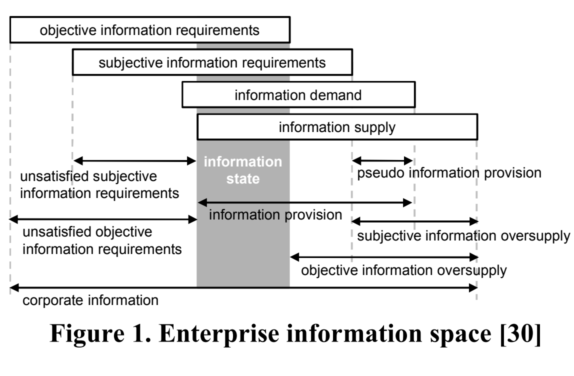

Figure 1. Enterprise information space [30]

This paper focuses on the alignment of objective and subjective information requirements as a specific aspect when designing analytical information systems.

The question as to what qualifies as "objective" information requirements is difficult to answer. With the exception of legally mandatory information, the question of objectivity is rather philosophical. Hence, we define objective information requirements as all information that are actually relevant to fulfill a decision maker's respective tasks in accordance with the company's objectives. Subjective information requirements in contrast are those information he or she believes to need.

The research focus is further narrowed to measures since they form *an* – if not *the* most – important part of the information supply for decision makers (as the phrase „you cannot manage what you cannot measure" popularly suggests) and their amount and availability has multiplied over the last decades [14, 29]. Although this limits the following approach to operational and repetitive decisions (compared to less standardized strategic decisions as e.g. on new plant locations), the majority of decisions in middle management is assumed to fall into this category. Furthermore, measures have been identified as feasible abstraction to reduce complexity and avoid information overload [27].

In summary, the following research question is examined: *"How should a system dynamics-based method supporting decision makers to (better) recognize their objective information requirements with regards to measures look like?"*

By relying on method engineering and a deductive approach, this paper outlines a method to identify and prioritize a decision maker's measure-based information needs thereby improving the alignment of objective and subjective information requirements.

The paper is structured as follows. Section 2 frames the issue by stating the research need from literature and providing required background information. Section 3 proposes and discusses a procedure model as central artifact. The model is evaluated in section 4 and its feasibility is exemplarily demonstrated using an existing SD model in section 5. Finally, section 6 summarizes the results, reflects on limitations and points out future research.

2. Background

Methods for information requirements analysis (IRA) are usually categorized into supply or data driven and demand or requirement driven approaches. Since the first rely on the reengineering of data schemas of transactional information systems, they risk stimulating information proliferation and waste resources due to unneeded information structures [30]. On the other hand, demand driven approaches start with informational requirements of decision makers – with the disadvantage that decision makers often struggle to specify their information needs exhaustively and unambiguously. To address this issue, various approaches as the analysis of business processes, the use of so-called business questions or techniques as task or document analysis, interviews and surveys (and combinations) have been suggested in literature [30]. For a detailed overview of various approaches see [28].

Subsequently, a recently published state-of-the-art article on IRA serves as basis to distill the need for action and derive those prerequisites that an answer to the research question must fulfill. Since one identified prerequisite is method support, elements of methods are introduced. Finally, related work using SD in general and performance measurement in specific is presented to provide the foundations for the proposed procedure model.

2.1. Information requirements analysis

Stroh et al. [28] provide an extensive state-of-the-art literature review covering publications dealing with IRA for analytical information systems from 1991 to 2009. Based on an examination of 97 English- and German-language articles they identify – amongst others – following five improvement needs.

Prioritization (N1). While many publications derive information needs from goal formulations, it remains unclear how information needs should be prioritized. Taking into account the described information proliferation, there is a strong need for action which has already stimulated many scientific contributions seeking for the right tradeoff between information overload and undersupply (see e.g., [20]).

Validation (N2). The validation of information needs with business users is rarely addressed – and if only by interviews. [28] suggest a more formal specification and validation using prototyping.

Documentation (N3). A comprehensive but intuitively understandable documentation of information needs is required, as [28] point out: "In practice, there is a strong need for models and documentations that can easily be understood by business and IT, without, however, losing precision in the specifications" (p. 40).

Process perspective (N4). Due to constantly changing company environments and the resulting evolutionary character of analytical information systems, a continuous identification, derivation and management of information requirements is necessary.

Method support (N5). While many existing approaches show characteristics of a method, they do not provide the required level of detail and remain too generic.

2.2. Method engineering

Since method support has been identified as one of the areas in need for improvement (N5), we subsequently present prerequisites of method engineering that will serve as evaluation framework in section 4.

Based on a literature review, Braun et al. [6] state that the appropriate construction of methods is an important scientific methodology within the design science approach. The "use of methods constitutes the basis for [an] engineering-based procedure" (p. 1296) and is characterized by four fundamental attributes: goal orientation, systematic approach, principles, and repeatability. Furthermore, they identify six fundamental elements a method description requires (specification document, meta model, role, technique, procedure model, and tool) and show that literature-based deduction – as chosen in this paper – is a feasible research method for method engineering.

Offermann et al. [19] extend this and other previous work aiming at increasing the utility of method design artifacts through a better comparability of its elements. They distinguish the following eight elements: ❶ purpose and scope (statements about the kind of output, the characteristics of that output, and the characteristics of the method itself), ❷ constructs (terms that need to be introduced, e.g. using a meta model), ❸ principles of form and function (description of the method following the chosen meta model), ❹ artifact mutability (the degree to which changes in the method itself or an instantiation of a method are foreseen), ❺ testable propositions (that refer to either "truth" or "utility" of a method whereby a design-oriented approach should primarily focus on the "utility" with respect to the purpose), ❻ justificatory knowledge (supporting transferability and validity, e.g. through referencing existing and accepted methods and/or theories), ❼ principles of implementation (meaning to implement a generic method in a specific situation), and ❽ expository instantiation (as e.g. a fictional example of an instantiated method in a specific situation). Although a full adoption of these ideas is not possible within this paper, we follow the structure as basis for our considerations. Thereby, we allow for later refinements to increase the comparability with other methods.

2.3. System Dynamics

The method proposed in this paper heavily draws upon SD, a methodology able to comprehensively identify, analyze, and simulate complex causal structures of managerial systems for the "design of improved organizational form and guiding policy" [12, 13]. According to Morecroft et al. [18], the application of SD models often results in revisions and adaptations of decision rules and learning effects in terms of future decision making. These enhancements are based on the consideration of time delays, nonlinearities, and non-intuitive feedback loops within the method (e.g. [25, 31]).

The frequently cited flight simulator metaphor [25] might help to understand the value of SD and its fit for IRA: On the one hand, pilots use simulators to learn more quickly to fly a real aircraft. But on the other hand, they also feed back their real-world experiences to improve the flight simulator – which in turn improves future trainings.

Since SD strives for the goal of "qualitative description and exploration as well as quantitative simulation and analysis for the design of complex system structure and behavior" [24], it can be used as "simulator for decision makers" where measures adopt the role of cockpit instruments. In this sense, a SD model helps a decision maker to realize his or her "true" information needs regarding measures and to value them appropriately.

There are two vital articles combining issues of performance measurement with SD. Santos et al. [21] suggest a combination of SD and multicriteria analysis to "make [different steps of] the performance measurement and management process more efficient and effective" (p. 1267). Sousa et al. [23] extend these thoughts and propose a structured engineering approach for conceptual design of enterprise performance measurement systems. Yet the level of detail remains quite abstract, a procedure model is missing, and the link to the company's objectives to derive more objective information requirements is not explicitly demanded.

So while SD can and has been used to support decision making [5] and it has been shown that the improvement of mental models of decision makers through SD models actually increases the quality of managerial decisions [15, 22, 26], approaches on how to include the possibilities of SD in IRA do not provide sufficient methodical support on how to derive and prioritize measures. This research gap is addressed in the following sections.

3. Proposition of a Procedure Model

A procedure model is the central element of each method [6]. Therefore, we subsequently present a procedure to derive the importance of measures. Thereby decision makers can realize what information actually are most relevant (objective information requirements) compared to those information he or she believes to be most relevant (subjective information requirements). We assume that through this learning process objective and subjective information requirements get "better" aligned.

3.1. Description

Since the suggested method is based on SD, we selected Sterman's [25] well-established iterative SD modeling process as basis. He suggests five stages: problem articulation, formulation of dynamic hypothesis, formulation of a simulation model, testing, and policy design and evaluation. The seven steps of our proposed method roughly coincide with this structure, whereby Sterman's second stage (formulation of a dynamic hypothesis) is further divided into the three steps B, C and D. Figure 2 shows an overview of the proposed procedure model.

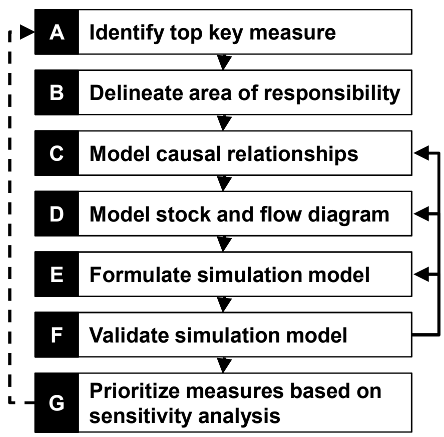

Figure 2. Procedure model

As a first step (A), the corporate objective system needs to be made explicit. We want to identify the informational requirements ("most important" measures) a decision maker requires to decide in line with its company's objectives. Hence, we define the importance of a measure as the degree to which it influences the achievement of a company's objectives.

Adopting a value-based management view all objectives must be ultimately linked to one or more financial measures (note that if more than one measure is established, an aggregated top key measure based on a weighting is required). This view seems appropriate since it is generally accepted as theoretical framework in economic research and enables the consistent evaluation of decision effects across functional areas and hierarchies [7].

In a second step (B), it is necessary to delineate a decision maker's area of responsibility and establish its link to the corporate objective system. The purpose of our SD model is to answer the following two types of questions: (1) To what extent does the variation of one variable (ceteris paribus) affect the top key measure? (2) To what extent does the variation of one variable require a decision maker to take corrective actions? While at first sight both questions seem exchangeable, the answers may be different as the example in section 5 will show.

Step B is of utmost importance since model boundaries set too narrowly will result in the exclusion of corresponding information requirements. On the other hand, a scope defined too broadly increases a model's size and complexity which disproportionately increases modeling effort and detracts attention from the essential underlying relationships. A so-called model boundary chart stating endogenous, exogenous and excluded variables can contribute to intersubjective comprehensibility of the system's delineation [25].

The third step (C) comprises the identification and modeling of causal relationships. Empirically observed correlations can serve as starting point to identify causal relationships. The set of all cause-and-effect-relationships between variables form the feedback structure of a system and are documented in a causal loop diagram.

The development of a stock and flow diagram is done in step D. The feedback structure is translated into the underlying physical structures (e.g. flows of material, money or information) [25] consisting of stocks and flows. Stocks are storage elements that can only be increased or decreased by flows. The strength of a flow is always regulated by exactly one valve. Flows connect either two stocks or a stock and a source/drain (i.e., unlimited stocks outside a model's boundaries). Converters are auxiliary variables that are used to regulate valves or alter other converters. These relationships are depicted by connectors (see also figure 3).

In step E, the simulation model is formulated through specification of equations, parameters and initial conditions in the stock and flow diagram. Equations describe the behavior of one variable depending from one or more other variables over time. In this step it is important to find the right balance between model accuracy and pragmatism. Since the models purpose is to identify the importance of measures based on a sensitivity analysis, it is necessary to start with realistic assumptions regarding parameters and initial conditions.

The sixth step (F) comprises the validation of the model. Different concepts and methods have been proposed for formal SD model validation. While validation of a model must also include semi-formal and subjective parts (e.g. in order to validate the fit to its purpose), we follow Barlas [2] argumentation who focuses on formal aspects of model validity and does not include philosophical aspects (while not neglecting them). Both structure (direct structure and structure-oriented behavior tests) and behavior (behavior pattern tests) validity can be tested. A direct structure test focuses on the formal soundness (e.g., a dimensional consistency test checks if dimensions on the left-hand side of an equation match the right-hand side). Structure-oriented behavior tests try to uncover structural flaws by wrong behavior (e.g., the application of extreme values causes an improper model behavior). Behavior pattern tests have been suggested to check if long-term patterns produced by the model match the observed reality. An extensive overview of possible tests can be found in [2].

The prioritization of measures is the last step (G). Figure 3 shows the meta model for stock and flow diagrams (as described in step D) following the notation for meta models suggested by [11]. Stock, valve and converter (sometimes also called auxiliary variable) elements are interpreted as potential measures (dyed grey) required by a decision maker.

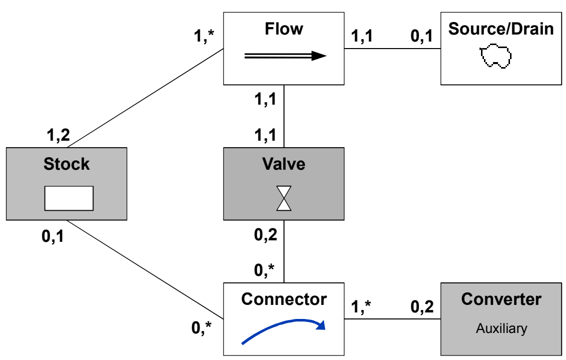

Figure 3. Meta model for stock and flow diagrams

For these elements, a sensitivity analysis is made. The goal is to identify the influence of (ceteris paribus) variations of one measure on the top key measure – considering the modeled time delays, feedback loops and nonlinearities. An isolated view based on simpler estimations (as e.g., rule of proportion) cannot reproduce these effects. Note that we refer to numerical sensitivity only (meaning that a change in assumptions alters the numerical values of other variables [25]) and do not consider behavior mode or policy sensitivity.

While the sensitivity analysis reveals the importance of a single measure with regards to its influence on the top key measure, the difficulty to obtain the measure is not yet considered. While one could argue that this is not part of the IRA, in a real-world setting decision makers will favor measures that can be made available in a timely manner and at no extra cost. In literature, prioritization approaches considering e.g. cost, implementation time, data quality and other aspects can be found in different combinations [30]. We aggregate these considerations to a single dimension called availability (a low availability would indicate that a high investment is required to automatically collect a measure or that manual work is required).

Figure 4 shows a 3x3 matrix integrating the two dimensions importance and availability. Based on an individual weighting a prioritized order of the measures can be established. In this case, measures would be sorted into three classes (indicated by different shades of grey – with darker shades indicating a higher prioritization). Companies may change this prioritization, e.g., to over-proportionally value importance over availability or to define a higher granularity of classes.

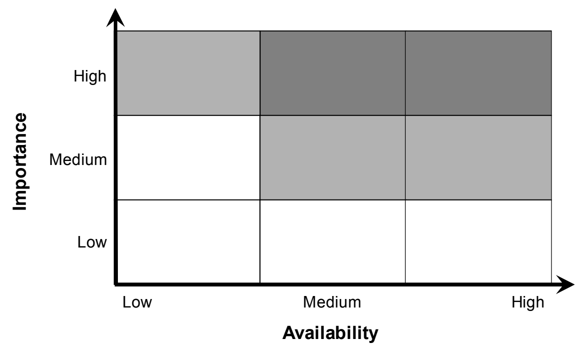

Figure 4. Prioritization matrix

3.2. Discussion

This section discusses advantages and disadvantages of the proposed procedure model with regards to the identified improvement needs for IRA.

Admittedly, the proposed procedure model involves a lot of manual effort and interaction between decision makers and analysts. Even if a suitable SD model is available as starting point, model boundaries and the link to corporate objectives need to be established or confirmed, initial values for an instantiation of the equations are required and the results have to be iteratively discussed triggering new adaptations of the SD simulation model.

On the other hand, all five described improvement needs can (at least partially) be addressed.

Prioritization (N1). The proposed procedure leads to a quantitative prioritization of all modeled measures. A numerical sensitivity analysis reveals a measure's influence on the top key measure. This demand-based prioritization is supplemented by a supply-based qualitative prioritization that has not been further detailed so it can be adapted to consider company-specific preferences (e.g., higher valuation of cost aspects compared to data quality).

Validation (N2). While the resulting artifacts as causal loop diagrams, stock and flow diagrams and simulation results cannot be seen as a prototype in its traditional sense, they show both structure and behavior of the interconnectedness of measures and hence build a kind of "informational prototype". A use of these artifacts in interviews may help to validate information needs in a semi-formal way.

Documentation (N3). The generated SD artifacts also fulfill documentation purposes: They are comprehensible without a mathematical or IT education and have been used for discussions with decision makers [15].

Process perspective (N4). This need does not refer to the iterations in the proposed procedure model but to a regular review of a decision maker's information requirements (indicated by the dotted line in figure 2). Since all required artifacts are already available and only changes have to be incorporated, the effort will be significantly reduced.

Method support (N5). While a procedure model is an important part of any method, other elements need to be considered as well. The next section examines what is missing to claim "full" method support.

4. Evaluation

In this section we use the eight elements Offermann et al. [19] suggested for evaluation to discuss the potential to extend the presented procedure model to a method.

➊ **Purpose and scope.** The method aims at facilitating the alignment of objective and subjective information requirements. It should be applied when decision makers suffer from information overload and struggle to appropriately value the importance of individual measures. Potential users are all actors involved during IRA, especially decision makers and business analysts.

The primary result is a list of prioritized measures that takes into account both importance and availability of a measure. A side output is the continual learning of involved decision makers about cause-and-effect relationships and interrelations thereby transparently revealing underlying assumptions that can ultimately also improve decision quality [15, 22, 26].

➋ **Constructs.** Constructs can refer to the method itself, its output or the enactment context [19]. While a meta-model for stock-and-flow diagrams following the SD methodology has been introduced and linked to measures, other terms and constructs (as e.g. a meta-model for the steps in the procedure model) have not been described due to its intuitive comprehensibility. Hence, a proper documentation of all constructs (that would go beyond the scope of this paper) is missing for a "full" method.

➌ **Principles of form and function.** This part coincides with section 3 which describes the procedure model as core element of any method. Again, the level of detail presented is not yet sufficient. For example, it remains unclear what roles have to interact how in order to derive the results for each step of the procedure model.

➍ **Artifact mutability.** We do not foresee changes in the method itself since all proposed steps are necessary. Leaving out a step would result in measures endangered of no reference to corporate objectives (in case of excluding step A), a model size no longer feasible (if step B is omitted), lower result quality (if leaving out step F), or no results at all (in case of excluding step D, E or G).

On the other hand, artifact mutability also refers to changes in the instantiation of a method [19]. Within the steps, variations are possible. While there is a need for a system of objectives, this has not necessarily to follow a value-based management approach (step A). Another example refers to step G. The final prioritization of measures can be altered in any favored way – reaching from a pure emphasis on information demand to a very high consideration of different aspects of information supply (as e.g. cost or data quality).

➎ **Testable propositions.** Since "a method is valid if it is useful in respect to the purpose" [19], a practical application still has to show that the method actually fosters a better alignment of subjective and objective information requirements. Even if the proposed steps are based on previous scientific results, match the existing body of knowledge and are convincing in its deductive logic, a real-world proof is missing.

Two scenarios can be distinguished to prove the utility. In the less severe one, the appraisal of decision makers would be sufficient. A possible setting would be to ask a representative group of decision makers with the same area of responsibility for a fix number of most important measures, run them through the procedure model and repeat the question. If the selected measures change and if the decision makers believe the new set would help to make better decisions in line with corporate objectives, the utility of the method would be assumed.

In the more severe scenario, a higher coverage of objective information requirements would need to be linked to a higher achievement of a company's objectives. This results from the previously introduced understanding of objectivity, referring to an improved information base to fulfill all tasks in accordance with the company's objectives However, it remains questionable if a resilient link to utility of the method can be established because side effects (as e.g. variations in decision quality) are very difficult to exclude.

➏ **Justificatory knowledge.** The proposed method heavily draws upon previous work in SD. The SD methodology has been existing for more than 40 years, has been successfully applied to various contexts (including but not limited to decision support in business environments) and reached a level of maturity where many models are already available and can serve as starting point. While it has often been criticized that model outcomes only reflect assumptions, the usefulness of models to influence and improve the so-called mental model of decision makers has been confirmed [25, 26]. The issue of model validity has also been extensively examined [2, 3].

Transferring und utilizing the SD methodology to improve IRA in the suggested way seems especially promising since humans tend to underestimate dynamic and non-intuitive behavior caused by delays, feedback loops and non-linearities [26].

❼ **Principles of implementation.** When the suggested method is implemented, iterations will be necessary to properly define the model's boundaries, identify variables and their relationships and create the simulation model. Furthermore, involvement of both decision makers and business analysts is required. The first have deep knowledge on the business context, the latter contribute the technical and methodical skills to translate it into the required models.

But while iteration and joint modeling are two principles of implementation, other principles are subject to further research. These would give additional advice on how to adapt the proposed method in a specific situation.

❽ **Expository instantiation.** Both the (fictional) derivation for a particular context and situation or a report on real-world execution of the method are possible instantiations [19]. Hence, the next section demonstrates the methods application for the case of a decision maker within a telecommunication company who is in charge of complaint management.

In summary, the main points missing to claim a "full" method are an extensive documentation including definitions of all terms and meta models, a proof of utility in a real-world setting, and further principles providing advice when implementing the method. While in principal, no road blocks have been identified, these issues must be addressed by further research drawing upon the ideas sketched in this paper.

5. Demonstration of Applicability

This section addresses element ❽, the expository instantiation. Subsequently, a fictional example based on a decision support model for complaint management proposed by Meier et al. [17] is presented. It is intentionally kept very simple to demonstrate the basic applicability and ease understanding of the underlying idea. Nevertheless, all steps can be scaled to match the complexity of real-world settings as SD models with more than 100 variables confirm [25].

The model assumes periodic revenues from a homogeneous customer segment as it can be found for data tariffs in the telecommunication sector. The central issue for the decision maker is the conflict between loss in company value due to defecting customers (churn) and loss in company value due to overinvestment in customer retention.

Subsequently, the procedure model is applied to identify the importance of measures and derive a prioritization.

Step A: Identify top key measure. The company strives for sustainable value increase. A suitable top key measure for complaint management is the so-called Customer Equity (CE), an aggregated measure representing the sum of values of all customers (quantified by their customer lifetime value). Following a value-based management approach, CE should be maximized (or a loss of CE minimized).

Step B: Delineate area of responsibility. The complaint manager only decides on the amount of compensation paid as a complaint solution. Since e.g. acquisitions of new customers are outside the decision maker's area of responsibility, marketing efforts or the number of new customers do not have to be part of the model.

Step C: Model causal relationships. Decision maker and business analyst jointly identify causal relationships. Figure 5 shows the resulting causal loop model for the example.

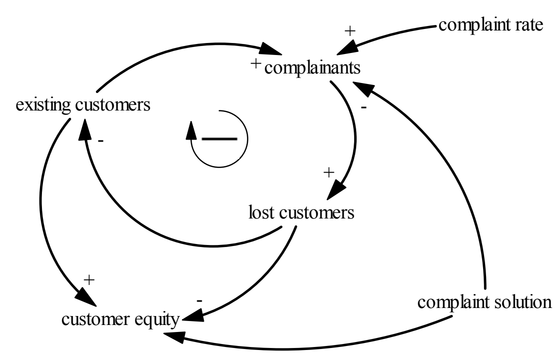

Figure 5. Causal loop diagram

The higher the number of existing customers, the higher the CE will be. But at the same time, more customers imply a higher number of complainants since typically a certain fraction of customers complain (complaint rate). But the complaint solution required to reduce the number of complainants also reduces the CE. On the other hand, the more complainants remain unsatisfied, the more customers a company may lose, which also would reduce the CE.

Step D: Model stock and flow diagram. The causal model is translated into a stock and flow diagram (see figure 6). The stock *existing customers* contains in each period the respective number of customers. Since acquisition was excluded the stock cannot grow but only be reduced by the flow *churn rate* – representing the part of customers defecting. The churn rate is influenced by four converter parameters: the *price* paid for a service, the number of customers complaining in each period (*complainants*), the amount of a (monetary) *complaint solution*, and the *expectation level* the customers have regarding the complaint solution.

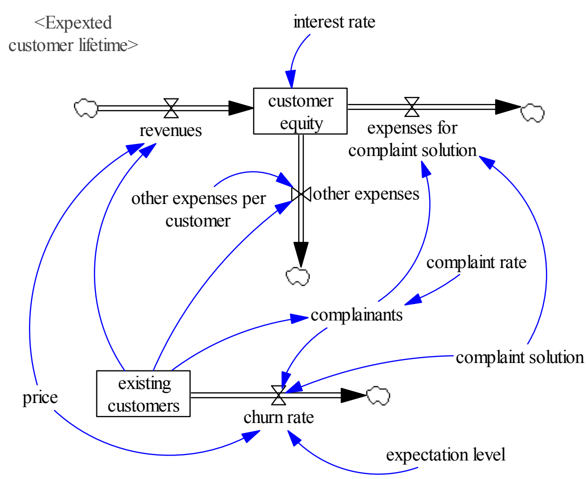

Figure 6. Stock and flow diagram (cf. [17])

The cause-and-effect relationship between complaint management and company value is modeled via the stock *customer equity*. It is increased by *revenues* (existing customers pay each period a price for the service) but decreased by *expenses for complaint management* (the complaint solutions paid to the complainants) and by *other expenses* (representing the production cost of a service). Additional details of the model can be found in [17].

Step E: Formulate simulation model. Differential equations, realistic parameters and initial conditions need to be defined for all model elements. Existing SD tools – as e.g. Vensim® DSS 5.9e – allow equations drawing from an extensive set of functions and distributions. In the complaint management example, [17] justify the equations by previous research results and empirical observations. Typical parameter values from the telecommunication industry are used to instantiate the model.

Step F: Validate simulation model. Prior to interpreting results, the model's validity must be examined. While the exemplary model passes structure tests (as dimensional consistency checks) and structure-oriented behavior tests (as feasible model behavior in case of applying extreme values), a behavior pattern test (as matching model predictions with the observed reality) or an empirical confirmation has not yet been published.

Step G: Prioritize measures based on sensitivity analysis. In order to determine the importance of measures, the effect of a parameter change of +/–10% on required corrective actions of the only decision parameter (complaint solution) and on the top key measure CE are simulated. This coincides with the two main purposes of measure-based reporting: ex-ante decision support and ex-post controlling [9]. Figure 7 shows the results of this numerical sensitivity analysis for most stock and converter elements. Valve elements and converter elements purely calculated from other converters are excluded. The reason is that in this case a change of +/–10% may be caused by different variations of upstream model elements. This is not considered as a bug but as a feature since it fosters systems thinking and requires a decision maker to focus on the root cause of an effect instead of relying on measures that are difficult (and hence error-prone) to interpret. Nevertheless, these measures might be used if upstream measures cannot (easily) be reported. In the example, the churn rate may be used as a fair proxy for the expectation level because a +/–10% variation of the expectation level results in a +5.3%/–5.9% change of the churn rate.

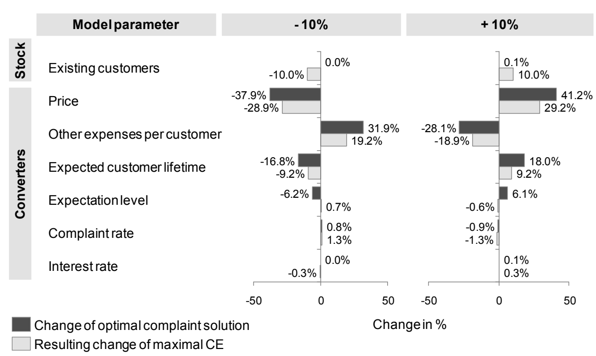

Figure 7. Numerical sensitivity analysis (cf. [17])

For prioritization purposes, three classes are distinguished: under-proportional (less than 5% change), about proportional (between 5 and 15% change), and over-proportional (more than 15% change) influences on either the top key measure or the necessary adjustment of the decision parameter. Data availability is selected as second dimension and split into three classes: low (manual or semi-manual data collection), middle (online availability), and high (online availability in high data quality and frequency).

In the example, the company adopts the prioritization matrix: Importance is higher valued than availability. Figure 8 shows the resulting matrix for measures of the simplified example. Judgment of data availability follows the assumptions of [17]. Measures resulting from valves may be added if they substitute a measure with low availability but high or medium importance (as in this case churn rate instead of expectation level). Note that the CE as top key measure is not part of the prioritization but should be reported as well while the decision parameter (complaint solution) is not reported.

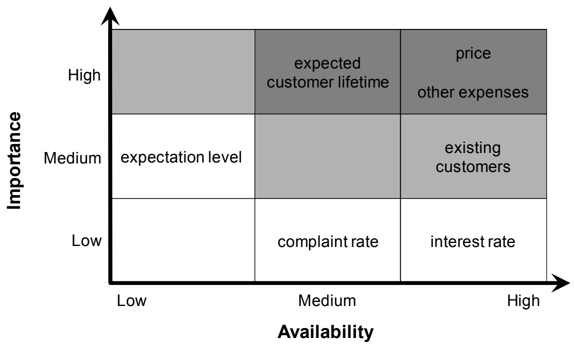

Figure 8. Resulting prioritization matrix

In summary, the example shows the feasibility of the suggested method to identify and prioritize information needs regarding operational and repetitive decisions in principle. It especially helps to emphasize on the right non-financial measures (in this case expected customer lifetime, expectation level or complaint rate) instead of often lagging financial measures [9] as revenues or expenses.

6. Conclusion, Limitations, and Outlook

The primary purpose of this paper was to outline the idea of a method to improve information requirements analysis for analytical information systems by using SD to identify and prioritize measure-based information needs of decision makers. We proposed a procedure model drawing from the SD methodology, showed how this would help to overcome current shortcomings in IRA, and referred to method engineering to evaluate how this idea can and must be further developed. While no fundamental road blocks have been detected, an extensive documentation of terms and meta models, a proof of utility in a real-world setting, and further implementation principles are missing and leave room for further research.

Admittedly, the suggested method entails some limitations that need to be critically considered. At first, the effort required to create the models and equations for a subsequent prioritization is very high. In comparison with other requirements engineering approaches it is probably too high if only their value for IRA is considered. But if existing SD models for decision support are used as starting point and if initially build models can be reused in similar areas, a cost/benefit consideration can (despite the high complexity) result in a positive result.

Secondly, the problem domain is limited to operational and repetitive decisions that rely on measures. While this category constitutes a significant share of decisions, other IRA approaches (as e.g. the use of business questions) do not face this limitation. Then again, the suggested SD-based simulation enables a comprehensible prioritization of measures based on a company's objectives that cannot be derived by existing approaches.

Thirdly, the sensitivity analysis relies on a ceteris paribus consideration. While this is a necessary simplification to prevent combinatorial explosion of simulations, it might hide effects occurring in case of simultaneous events changing many measures at the same time. How to properly address this issue should also be addressed by future research.

Fourthly, every model necessarily is an abstraction and therefore simplification of the real-world. Its output quality heavily depends on the input quality. Hence, results need to be carefully checked with respect to its fit for the intended purpose.

But despite these limitations, the proposed method sketch demonstrates the potential of SD to contribute to the alignment of objectively required and subjectively believed to be required, measure-based information needs of decision makers.

7. References

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