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Abstract

The rise of the service economy is increasingly reflected in the IS discipline. Since services depend on a co-creation of value between service providers and customers, productivity measurement needs to account for both points of view. Contrasting this evolution, current productivity management concepts often remain limited to the firm instead of focusing on dyadic relationships. Also, software tools frequently constitute expert systems that are focused on solving an optimization problem based on a linear program, but do not guide users in setting up a suitable productivity model in the first place. To account for this need, we conceptualize a software tool support for setting up productivity models for services. Our concept encompasses an extended Data Envelopment Analysis (DEA) approach as its analytical core, but in addition features various tools that help users to collaboratively define a productivity measurement model. Since the suitability of such a model is contingent on the environment in which it is applied, the proposed concept constitutes a meta-design that is intended to be applicable to a class of productivity management problems. As an outlook we present ideas for further research focusing on the implementation and evaluation of IT artefacts compliant with the proposed meta-design.

Keywords: Productivity Measurement, Service Science, Data Envelopment Analysis, Design Science

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1 Service Productivity Management

Measuring service productivity is a topic that profoundly impacts research as well as practice. With the rise of the service economy that we have been witnessing in the recent decades, the competitive positions of firms, ecosystems of firms, and entire economies depend on continuously increasing productivity in service operations (OECD, 2005). Service productivity is closely related to the application of information systems, since "the service sectors with the highest rate of productivity growth tend to be those that invest more in ICT" (OECD, 2008).

However, due to their basic properties, measuring service productivity is more difficult to perform than measuring productivity in manufacturing. The most widely cited conceptualization comprises the so-called IHIP criteria, emphasizing that services are intangible (i.e., not physical), heterogeneous (i.e., co-created with the customer which leads to different service outcomes), inseparable (i.e., services are created and instantly consumed), and perishable (i.e., unutilized resources are inevitably lost since service cannot be inventoried). For more information see the literature review conducted by Zeithaml, Parasuraman, Berry (1985) and also the discussion in Lovelock and Gummesson (2004). As a consequence of these distinctive attributes, the concept of productivity management has to be adapted to account for a sound productivity management in the service sector. In particular, two aspects have to be included into the productivity calculus: First the (perceived) quality of service has to be accounted for, since it is closely intertwined—and often conflicts—with economic resource utilization. Second, demand variability has to be accounted for, since a service cannot be stored. Instead, often the resources utilized in a service process are stored (a phenomenon often manifesting in queues). Both directions delineate a shift of the focus of productivity calculations, moving from the firm to the dyad of the firm and its customer as the object of analysis.

Propelled by recent break-through innovations in IT, the emergence of global service networks adds to the general problems of conceptualizing and measuring service productivity. Companies find themselves faced with the need of comparing the productivity of their service business units (or other companies, if situated in a network) internationally, for instance to reason about outsourcing (or even off-shoring) management decisions. This is far from being a trivial problem, since what constitutes productivity might be conceptualized differently in any setting, contingent on different service environments, industry characteristics, or cultural values.

Currently, productivity management lacks methods and software tools to account for these needs. Having its roots in the manufacturing discipline, the standard approach is to compute the productivity of a business unit by dividing the sum of weighted outputs by the sum of weighted inputs (Farrell, 1957). However, this approach suffers from two major deficiencies (Cook and Seiford, 2009, Farrell, 1957): First, due to the difficulty of combining multiple inputs into one measure for productivity, average measures were computed for each single input, ignoring all other inputs. Second, a weighted average of inputs was compared with output. These weaknesses led to the development of the Data Envelopment Analysis (DEA) approach (Charnes et al., 1978) that can now look back on more than 30 years of scientific history (Cook and Seiford, 2009) in the operations research discipline. DEA constitutes a non-parametric approach towards productivity management that can deal with several inputs and outputs simultaneously and does not require weights of inputs and outputs to be given a priori but determines them using linear programming. The DEA approach constitutes a benchmarking approach of so-called Decision Making Units (DMUs) and compares them against each other. The result of the DEA-approach is a relative measure for the DMUs' productivity on a percentage basis.

Although the history of DEA-related research is impressive, leading to far more than 4,000 publications from 1978–2007 alone (Emrouznejad et al., 2008), software tools that have been developed in this area (Barr, 2004) constitute expert tools that can hardly be used by untrained employees, and usually feature no functionality beyond formulating the optimization problem in a mathematical way and solving the linear program. It can be expected that additional functionality that is situated around the actual linear program can propel the diffusion of DEA into the productivity management of service companies, speed up the overall analysis process, and might lead to superior decision quality due to more adequate productivity models.

In this paper, we therefore present the conceptualization of software tool support that assists a user in defining and solving a suitable productivity model for a firm's service operations. We propose a method to rigorously select or develop context-specific productivity models, in line with the meta-design approach (Walls et al., 2004). The meta-design approach accounts for the need to develop solutions for classes of problems that remain valid outside individual environments, since, by definition, design is contingent on the properties of the environment in which an artefact is intended to function (Alexander, 1970).

The remainder of the paper is structured as follows: In section 2, a theoretical grounding for dyadic productivity analyses is presented based on reviewing some concepts that have been proposed in the service science literature on productivity management. Once defined, a productivity model can be calculated based on solving a linear program. Therefore, section 3 features the related work on DEA that has been exhaustively addressed in the operations research literature and will serve as the analytical core that is used to achieve this. A focus is set on taking service quality and demand variability into consideration, which are two important constructs to consider in a service context. In section 4, the meta-requirements for setting up a suitable productivity model with a software tool for service productivity management are identified. In line with design theory (Hevner et al., 2004) the design of IT artefacts needs to provide utility in its context, but still needs to be adaptable to other cases, thereby addressing a class of problems. Therefore, we present a meta-design (Walls et al., 2004) that can guide the design of various IT artefacts, such as a software tool for cooperatively defining productivity models. We conclude the paper by outlining a research process (Peffers et al., 2008) to design and evaluate IT artefacts that are compliant with our meta-design.

2 Theoretical Grounding

Productivity measurement in general requires the identification of meaningful input and output parameters (Charnes et al., 1978) on which the calculations can be based. The suitability of input and output parameters is contingent on the objectives the analyst wants to reach with the calculation and on the environment in which the calculation is performed.

One such contingency is the industry in which a firm is situated. In the service sector, productivity measurement needs to account for the distinctive properties of services (see section 1), which are still debated heavily in the service science discipline. Quite recently, the academic discussion about the commonalities and differences of physical goods and services has focused on outlining that—although not to be distinguished dichotomously (Engelhardt et al., 1993, Vargo and Lusch, 2008, Castells, 2010, Teboul, 2006)—a key difference is that services require the integration of customers (co-creation of value) while manufacturing does not (Sampson and Froehle, 2006). Therefore, it is not beneficial to think about service productivity only from the point of view of a service firm. Instead, service productivity has to be conceptualized and measured at the dyad level, comprising of a service firm and its customer(s) also.

Accounting for this focus, Grönroos and Ojasalo (2004) proposed a model for conceptualizing the productivity of services (Figure 1). On the input side, the co-creation of value is accounted for by distinguishing resources introduced by the service provider from resources introduced by the customer. These inputs denote any resources necessary to perform the service process, encompassing information systems, personnel, information, time and so forth. The utilization of these resources constitutes the internal efficiency (or cost efficiency) of a service.

Based on utilizing the input factors, the activities contained in the service process are carried out. Notably, activities carried out by the service provider in isolation are separated from activities carried out by the customer in isolation, and from activities that need to be co-created by both stakeholders.

From a productivity management perspective, this distinction is important, since the interface of a service provider with a customer might consume additional resources for integrating business processes across organizational boundaries. Also, activities conducted in cooperation with a customer are subjected to different types of customer variability (e.g., arrival variability, request variability, capability variability, effort variability, subjective preference variability) (Frei, 2006) which can make them prone to additional inefficiencies. Some of these factors, such as arrival variability, influence the capacity efficiency (or capacity utilization) of a service.

The result of a service process is an output, determined by two components. First, output quantity denotes the magnitude of output that is rendered by a service process. Second, the quality of the service as perceived by a customer is crucial, since services tend to be intangible and can often hardly be measured in terms of quantities (think e.g., of the difficulty in determining the quantity of "security" provided to citizens by the police). The abovementioned two factors determine the external efficiency (or revenue efficiency) of a service.

Service productivity is a function of all of the three efficiency factors. Notably, the three sub-constructs are not independent from each other, but are closely interconnected. For instance, maximizing internal efficiency would require that a service firm attempts to minimize its own inputs of the service process. Two conceivable strategies in order to achieve this would be to outsource some activities to the customer (e.g., by self-service technologies) or to streamline the service process by leaving out activities or conducting them with fewer resources. Although these strategies increase productivity at a first glance, they might come at the cost of lowering the external efficiency, since a customer might be unwilling or unable to perform additional activities in a service process, or might perceive the quality of service to be lower than before. Therefore, the overall productivity of the service might actually even diminish, although internal efficiency has been increased.

For productivity measurement in real-life situations, these considerations imply that for each individual context, the inputs and outputs of a service process need to be purposefully balanced, in accordance with the properties of the service system and its environment.

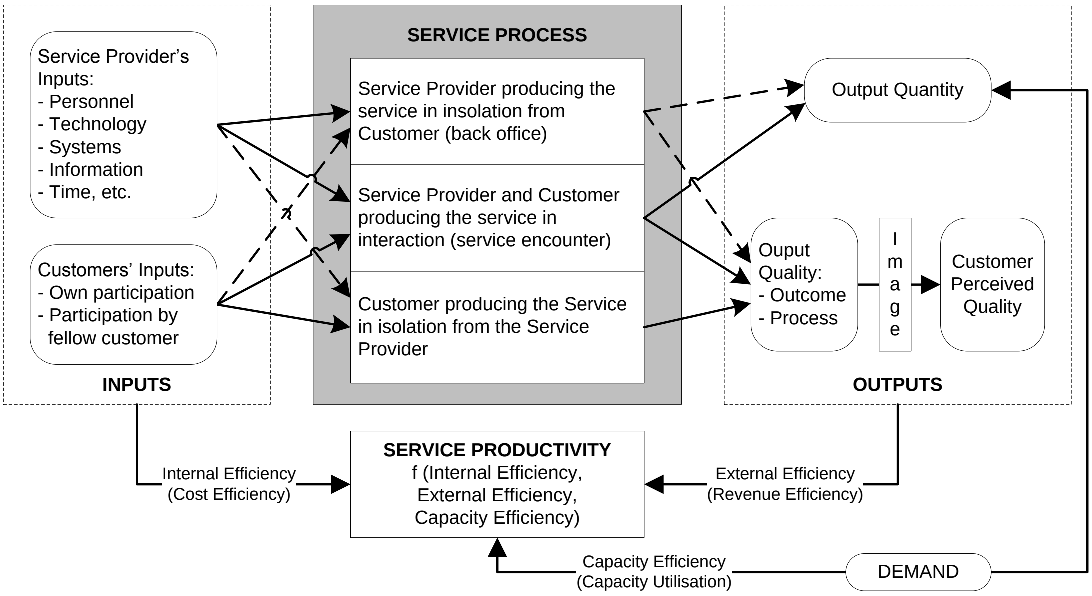

Figure 1. Service productivity model of Grönroos and Ojasalo (2004)

3 Concepts of DEA for Service Productivity Measurement

Parametric and non-parametric frontier models have been proposed as approaches for measuring service productivity (Emrouznejad and De Witte, 2010). Parametric frontier models need a priori theoretically founded assumptions about the functional form of the underlying production function. This is their main drawback, since often the underlying function is unknown. Therefore selecting a specific production function is hard to argue and to asses, as it is for example the case with the well-known Cobb-Douglas production function (Emrouznejad and De Witte, 2010). Non-parametric models, in contrast, do not need any a priori assumptions about the function. On the other hand, they suffer from the "curse of dimensionality" since the more inputs and outputs (dimensionalities) in the productivity measure are used the more observations are needed. In return, the production function is empirically identified from the observations.

For our research we have chosen the well-known and flexible DEA approach, which can be applied in a variety of different scenarios without requiring further a priori assumptions. DEA is used for the measurement of relative productivity—called efficiency in the DEA context—between similar entities, denoted Decision Making Units (DMUs) (Charnes et al., 1978). A DMU uses multiple inputs and converts them into multiple outputs. Based on the inputs and outputs, DEA estimates an efficient frontier, which is defined by the "relatively best" DMUs. By calculating the distance to this frontier for each DMU the efficiency is computed. In the mathematical model efficiency is a quotient of weighted inputs and outputs and these weights are optimized under some restrictions for each DMU. An efficient DMU has a relative efficiency of 100% and a DMU with a smaller value is judged inefficient. DEA identifies for each non-efficient DMU an efficient reference which uses less input to produce the same output (or produce more output while using the same input).

As discussed in section 2, incorporating quality into service productivity measures is of utmost importance to ensure that management decisions do not sacrifice quality standards for operative efficiency. However, including measures of quality into the productivity model is not straightforward as, due to the automatically chosen weightings for the in- and output factors. DEA would neglect quality for certain DMUs which will then be 100% efficient regardless of their quality level. Therefore several modifications to DEA have been developed, see (Shimshak et al., 2009).An obvious remedy to this problem is to create two separate DEA models, one measuring performance with respect to quality, the other with respect to operations. Then, the identification of DMUs fulfilling certain minimum requirements with respect to both dimensions can be identified (Soteriou and Zenios, 1999). Another way to handle quality factors is to apply so called multiple objective DEA, where again different models are created for quality and operative performance, but this time both models share certain in- and output factors. The weights of both models are then tied to each other such that they must assume similar values in both models. This way, the two separate models are integrated (Shimshak et al., 2009).

Besides quality issues, conventional methods applied to measure service productivity also suffer from the fact that services cannot be stored which implies that the productivity of a DMU depends to a large extent on the demand for the service it provides. Again, DEA models addressing this problem can be found in the literature (see (Chiou et al., 2010) for an overview that we rely on in this paper). Their main idea is to separate the production process into two phases. In the first one the input factors are compared to the potential output that could have been generated if demand was equal to production. Thus, this phase aims at measuring the production process unbiased by any up- and downturns of demand. Then, in the second phase, the potential output is compared to the output that is actually consumed by the customers. This way waste of potential output is quantified separately. Many different DEA-approaches exist to handle such two-stage models. The simplest one is to treat each phase as an individual DEA model. To prevent problems with computation of multiple models one can use approaches presented in (Chiou et al., 2010) which formulate models combining efficiency measures for both phases and an overall efficiency measure in one optimization procedure.

While DEA is, from a methodological point of view, a well-researched topic, there are few guidelines describing how to arrive at a proper productivity model, i.e. at an appropriate set of in- and outputs. Frameworks guiding the DEA researcher through a DEA application merely state that the set should be created carefully. Their focus however is on methodological implications (Avkiran, 1999, Emrouznejad and De Witte, 2010). Thus, our aim is to provide a holistic support of the entire service productivity measurement process of which DEA is only one step. Existing frameworks particularly suited to the service industry do exist. For instance, (Sahay, 2005) provides a methodology do identify appropriate factors by first examining the goals of an organization, then analysing objectives on the department level in detail, generating a candidate list of factors from the gathered information and finally condense this list to a final set. However, this framework does not provide any particular suggestions for how to be applied. Hence, we will, in the next section, work out the details of how to support a development.

4 Meta-Requirements for Setting up Productivity Models

Design science research literature states that rigorous design needs to account for a class of problems in order to be valid outside the boundaries of its original environment (Hevner et al., 2004). One approach that can be applied to achieve this is the meta-design approach, consisting of three subsequent sub-steps. First, a kernel theory is identified to substantiate the design process. Second, from the constructs provided by the kernel theory, so called meta-requirements are identified and systematized that need to be addressed by the properties of the artefact. Third, a meta-design is created to account for the identified meta-requirements. Since any artefact designed with compliance to the meta-design will correspond to the identified meta-requirements, the proposed meta-design accounts for a class of problems rather than to the subtleties of any individual application scenario encountered.

In accordance with the meta-design approach, we use the service productivity model of Grönroos and Ojasalo (2004) as the theoretical grounding that needs to be accounted for during the meta-design process. Subsequently, we will now identify meta-requirements for a software tool that can be used to set up a suitable productivity model for any service scenario, in line with the theoretical grounding. In chapter 5, we propose the meta-design for IT artefacts that comply with the identified meta-requirements.

In the following, six meta-requirements are identified for setting up a general productivity model in the service discipline to be solved with the non-parametric DEA-method.

R-1: The productivity model has to be specified in the form of inputs and outputs

The concept of productivity, even for services, encompasses the transformation process of inputs into outputs (Grönroos and Ojasalo, 2004). This concept must be presented as inputs and outputs to be suitable for non-parametric analysis (Emrouznejad and De Witte, 2010). Inputs and outputs are typically measured as quantities, e.g. “number of employees” or “sold products” that have a series of relevant attributes. For example, they can be either within the benchmarked service provider (the “internal factor”) or external sources as for example the customer (the “external factor”) (Grönroos and Ojasalo, 2004). The internal factors can be influenced by the service provider, whereas the external factors cannot, since they are controlled by the customer.

R-2: Long-term knowledge must be provided by the platform in an adaptable way

The artefacts of knowledge, used to measure productivity, are represented in productivity models or studies on productivity factors. The former are used in single application domains to measure productivity, for an exemplary overview in the public sector, see (Jääskeläinen, 2009). They provide knowledge on productivity in a particular domain (e.g. project management) or in an industry (e.g. public services) or a combination of these. For example productivity models in the software industry massively relate on measures based on outputs as lines-of-code, function points or process-runtime and bug-counters (Trendowicza and Müncha, 2009) and inputs such as budget or effort (Maxwell, 1996). However, not all productivity studies are technically mature enough to differ factors, Jääskeläinen (2009) names some that just mention important factors and leave the input/output interpretation with regard to productivity unanswered. In addition, He et al. (2008) have found evidence that productivity-factors in software development are determined by organizational and cultural factors such as project size, business area and language. On top of this, productivity is "highly variable across the […] industry of the software project" (Maxwell, 1996). We assume discovering and comparing productivity factors across industries, cultures and domains helps finding a common notion of productivity. This domain-knowledge should be utilized and reused in a way to deliver a template for a productivity model in a particular domain.

R-3: The platform must provide means to collaboratively develop a productivity model

In the run-up to performance measurement projects, it is important to gain a common understanding of the objectives, the transformation process and the requirements from the involved stakeholders (Emrouznejad and De Witte, 2010). In particular, any input- and output-factors need to be negotiated among the heterogeneous, physically and chronologically distributed group of stakeholders in form of a distributed requirements negotiations (Damian et al., 2008). As argued by (Edvardsson and Olsson, 1996, Smith et al., 2007) we focus on three types of discussions amongst stakeholders that are prone to misconceptions. Firstly, concerning the discussion within the group of decision makers, the importance of defining a common notion of productivity becomes apparent when considering the different definitions in the political economics (Melitz and Ottaviano, 2008), the engineering community (Triantis, 2004) and the ongoing debate in service science (Vargo and Lusch, 2008). Secondly, a discussion of the decision makers with operative business process experts improves the knowledge of the underlying transformation process and gains “potential benefits, such as a more in-depth analyses, additional insights and a broader range of operational characteristics” (Emrouznejad and De Witte, 2010). Thirdly, a discussion with customers reveals the customers' needs and expectations both necessary to specify and measure the perceived quality and quantity of the transformations' outputs. As services are provided in a reciprocal process—called co-creation of value—it is of utmost importance to also reflect the customers' contribution in form of dedicated inputs. Hence, customers information, inquiries and complaints (Grönroos and Ojasalo, 2004) have to be considered in the discussion and integrated into the model in the form of input factors.

R-4: The effort to acquire appropriate data must be considered in a decision support component

The necessary information for developing a model to measure productivity is restricted by the data that is available. When comparing factors as required by R-2 and R-3 against the available data, it is likely that data is missing, such that the requirements to be included in the model cannot be satisfied. Therefore, the productivity model must feature flexible mechanisms to conduct meaningful benchmarks in the presence of missing data. The other option for coping with missing data for productivity benchmarking is to put business procedures or information systems into place to obtain these data. In addition, a subset of the missing data might be obtained from processing existing datasets. For example, information concerning inputs (e.g. requirements) and outputs (e.g. the level of satisfaction) is crucial to calculate the productivity in a service setting with the DEA approach, but might be scattered in data repositories of the service provider and the customer. Since selecting an appropriate strategy for dealing with missing data constitutes a decision problem that is highly depending on the costs associated with each of the strategies, a business evaluation must be supported by the tool in order to identify the most adequate strategy.

R-5: Any decisions, made in setting up the productivity model, must be documented and archived

During the process of setting up a suitable productivity model cooperatively by service providers and customers, design decisions have to be made that highly influence the productivity model designed. During the design process, the stakeholders involved might pursue their own interests, such that, in the end, the resulting productivity model is the result of a negotiation process. As they originate from various stakeholders (R-3) and different environmental parameters (R-2 and R-4), the requirements must be documented in order to archive the design process in a traceable fashion. This process needs to account for two directions: On the one hand, each unique requirement is brought to bear on the design that implements it (forward). On the other hand, a design has to be traceable back to the design decision that was made to implement it (backward). However, it is insufficient to focus solely on single stages of the development process. Rather a full documentation of versions and the reasons for underlying change requests have to be documented to ensure user acceptance after the implementation and coherencies of argumentation can be reproduced. With this documentation, the involved stakeholders might be more likely to perceive the productivity model as ‘fair’.

R-6: The created productivity models must be transformed into a quantitative DEA-model

Compatibility to a solvable quantitative model is an essential design requirement to calculate productivity measures from the specified inputs and outputs of the productivity model. This requires converting the inputs and outputs by utilizing predefined transformation routines. This automatic transformation process has to support the various forms of productivity factors and to convert them in an appropriate quantitative model, based on the DEA-method and its extensions. In addition, a checking-routine can be implemented to detect and highlight any incompatible parts of the productivity model with the selected DEA-method.

5 Meta-Design

In this section, we describe the meta-design (i.e., a class of artefacts) to meet the meta-requirements identified above. Importantly, our meta-design does not address any specific artefact but refers to an entire class of artefacts , consistent with the design theory by (Walls et al., 2004).

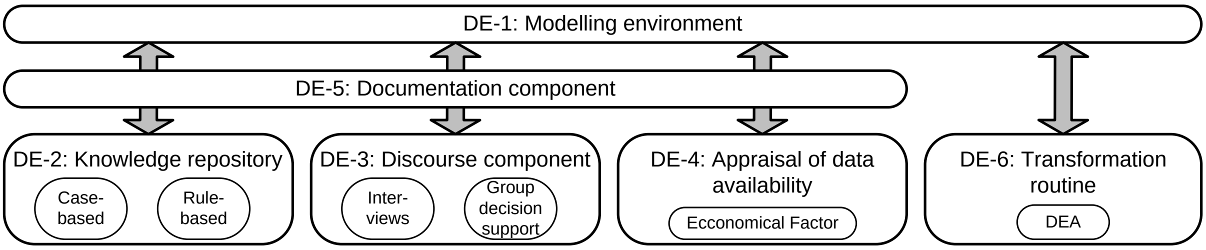

Figure 2. Structure of the proposed meta-design

Subsequently, the meta-requirements R-1 to R-6 are tackled by a set of design elements that form an interconnected framework, the meta-design in figure 2, made up of the following components:

DE-1: Modelling environment

The basis of the meta-design is formed by a modelling environment (DE-1) that acts as a repository and model editor with a common modelling language. This language incorporates *inputs and outputs* that can stem from *productivity factors*, used in already existent *productivity models*. This allows incorporating various productivity models and allocating their factors to either inputs or outputs. In addition, the modelling environment supports the specification of additional interpretable information regarding the inputs and outputs for the transformation process (R-6). Output factors may be highly dependent on customers' demand and therefore have to be treated in a special way, to differ between physical products (which are storable) and services (which are non-storable). This implies that the productivity depends not only on the ability to produce, but also on the customers’ demands. To prevent this peculiarity from skewing the analysis, both value propositions have to be treated separately, for example in a two phase production approach, described in section 3. Besides, Grönroos and Ojasalo (2004) integrate quality into service productivity measures to prevent quality standards being sacrificed for operative efficiency. Due to this, service-quality can be considered with "multiple objectives DEA" as stated in section 3.

DE-2: Knowledge repository for productivity models

As the knowledge that is already present in productivity models with explicit and implicit inputs and outputs, they should be utilized for further productivity measurement projects and therefore stored in a knowledge base. Due to the high numbers of available productivity factors in this knowledge base, a modus for selecting suitable ones has to be established. Therefore we refer to two approaches: rule-based configuration and case-based selection (Russell, 2010) of appropriate models. The former unifies the present models and uses rules to align it to the case on-hand by iteratively parameterising the rules and therefore limiting the solution-space. For instance, by selecting "project management" for the particular rule that configures "domain" and "software engineering" for the rule that configures "industry", specific factors emerge that are, according to the knowledge base, especially suited for measuring "management of software projects". For example, some of these factors might be "degree of reuse", "project schedule" and "domain experience" (Wagner and Ruhe, 2008). The latter method selects appropriate productivity models from the knowledge-base by "utilizing the specific knowledge of previously experienced, concrete problem situations", in this case the selection of productivity models. This case-based method has its roots in work related to artificial intelligence and the works of Schank (1982), and follows a four-step process: first the case on-hand (the productivity model) is described with respect to its features, then the knowledge-base is searched and for each element a measure of similarity is calculated, using selection criteria like "domain", "industry" and similar productivity factors.

DE-3: Discourse component

The three discussions mentioned in R-3 fulfil two purposes: discovering new factors that might be suitable as inputs or outputs for the productivity analysis and checking whether already known productivity factors suggested by the knowledge base (DE-2) can be adapted. The first involves analysing operative processes to gain specific domain-knowledge of the transformation process and discover previously unknown factors. These could for instance, be inputs hidden in the transformation process or factors that define the customers perceived service quality. We suggest interviews as a first step to elicit important factors and their attributes mentioned in R-1 (Hull, 2010). This encompasses especially negotiating, documenting and measuring the inputs that the customer contributes within the dyadic relationship to the service process. In the second step, the collected factors suggested in DE-2 are prioritized based on a discourse involving stakeholders from management and business operations. Therefore, a process is required to manage and steer the negotiation-mechanism. Requirements engineering's uses group decision support systems to enable "group modelling" that tackle similar problems like different concerns in a group and unstructured, complex tasks (Yihwa and Minder, 1993). Another study on requirements negotiations (Damian et al., 2008) indicates that, in general, negotiations are more effective when conducted asynchronously to remove uncertainty. After the discussions with the three stakeholder-groups, it may be the case that similar factors have been collected during this process (e.g. "lines-of-code" and "number-of-software-classes"), requiring a process to screen them and drop factors that convey information included in other variables. This prevents the analysis from overweighting a certain scope (in this case the volume of code). One approach to achieve this involves judging the list of variables by expert decision makers (Golany and Roll, 1989). In addition, reducing variables is particularly crucial since a great number of inputs and outputs dilutes the DEA-models results and leads to the “curse of dimensionality”.

DE-4: Appraisal of data availability

Once missing data has been identified, for example by comparing the required information against the meta-data of the business-warehouse, several strategies for compensation are available. First, to replace missing data, factors that are measuring about the same objective can act as a replacement for each other. Generally suitable are redundant factors as discussed in DE-2 (e.g. "lines-of-code" can be replaced by "number-of-software-classes"). Secondly, to obtain additional data, external sources like statistical databases, annual accounts or price information can be consulted (Emrouznejad and De Witte, 2010). Thirdly, information lying within the domain of the customer must be acquired and integrated into the benchmark. Customers' inputs have to be negotiated and documented in contracts and can then be measured in the requirements engineering process. As the valuation of outputs is significantly determined by the customers' (subjective) perceived quality, interviews and surveys on his satisfaction must be conducted. However, these three strategies generate costs that economically have to be assessed against the potential benefits. Therefore (Zhu and Wu, 2005) introduce the Economical Factor that integrates the cost and the importance of a factor, to obtain only those with the best information/price-ratio.

DE-5: Documentation component

The application of long-term-knowledge to construct and modify productivity models, the discussion amongst stakeholders as well as the evaluation from an economic point of view, considering especially aspects of data availability, lead to decisions of aligning or rejecting a specific productivity model. It is therefore the task of the comprehensive documentation component to record the different model versions and the subjacent decisions. This encompasses all elements specified by the modelling language that are stored within the model repository. The reasons for this can be deduced from the concept of issue-based information systems (IBIS) (Kunz and Rittel, 1970) and (Shum et al., 2006). In accordance with IBIS, every issue in a repository should be documented with a position each of which is associated with alternative positions. These in turn are associated with arguments which support or object to a given position. These arguments might be discussions among stakeholders, long-term-knowledge and economic aspects of data availability by which means the aforementioned elements of the meta-model are integrated. As a last step of such a guided discussion, the final conclusion has to be marked and used for the model construction. This approach helps to make the design process traceable for observers as well as participants.

DE-6: Transformation routine

The completed productivity model has to be transformed automatically to a solvable DEA model which is able to handle the special aspects of the productivity model. The usage of demand or quality, as mentioned before, or the usage of undesirable outcomes of a transformation process (e.g. pollution) needs special adaptations of the “classic” DEA model (Scheel, 2001). Therefore the productivity model was extended with interpretable attributes in the modelling environment (DE-1). A representative example is the specification of undesirable outputs in the modelling environment by attributing the output. These additional attributes are used to automatically choose the accurate adaptations of the quantitative model which will assist the novice DEA user to specify an appropriate model. After the model transformation, the quantitative DEA model is computed by a linear program solver and returns the productivity measure for each DMU. Before that, the supplied data for the productivity model should be checked for pitfalls described in (Dyson et al., 2001).

6 Outlook

In this paper, we present a framework for productivity measurement in the service science discipline using the DEA-method. In accordance with explanatory design theory by (Walls et al., 2004) this framework is constructed to meet a set of requirements (R-1 to R-6) that were deduced from the relevant literature on productivity. As we do not develop a specific artefact but address a whole class of problems, our framework constitutes a meta-design (Walls et al., 2004). It consists of six design elements (DE) each of which complies with one respective requirement. These are meta-requirements and therefore incomplete to focus on the main issues in this field of research. They form a universal class of design problems, "to explain a range of phenomena rather than a specific instance" (Baskerville and Pries-Heje, 2010).

The contribution of this paper is to allow for the development of instances of the meta-design that are suited for the collaborative and distributed specification of service productivity measure. Service providers and customers can work collaboratively together on the tool-based conceptualisation of the productivity measures. We believe that this has important implications regarding the acceptance and practical relevance of the productivity measurement approach.

Our future research agenda focuses on implementing and evaluating the software tool for the specification of service productivity measures in a globally distributed service setting. With respect to the design science research process, proposed by Peffers et al. (2008), the development of an instantiation leads to the evaluation of the meta-design in real world-scenarios.

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