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appears in: Journal of Decision Systems, 2018

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WI-645

Maturing Maturity Models –

A Methodological Extension Using the Analytical Hierarchy Process and Google PageRank

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Abstract

Maturity models are used in various application domains, as they provide well-structured overviews about companies' as-is situations in a certain discipline due to applying different stages of development. However, maturity models face criticism. Most maturity models structure only their respective field of activity without adding value for decision-making purposes. There is a lack of models for prescriptive purposes that help derive and balance concrete improvement measures. In addition, maturity models are criticized for oversimplifying reality. To address this gap, we propose a methodological extension to enhance maturity models, such that they explicitly account for the importance of multiple capability areas and consider the impact of the interactions among capability areas. To do so, we combine methods from multi-criteria decision-making, that is, the error-adjusted Analytical Hierarchy Process, and from network analytics, that is, the Google PageRank.

Keywords: Maturity Models, Analytical Hierarchy Process, PageRank, Corporate Decision-Making.

1 Introduction

Maturity models have a long tradition in research and industry (Pöppelbuß, Plattfaut, & Niehaves, 2015; Rosemann & De Bruin, 2005; Van Looy, De Backer, & Poels, 2011). Based on the assumption of predictable patterns of organizational evolution and change, maturity models typically represent theories about how an organization's capabilities evolve along an anticipated, desired, or logical path of predefined stages (Pöppelbuß et al., 2011; Van de Ven & Poole, 1995). Applying these stages enables evaluating an organization's capabilities regarding a certain discipline or company goal, and thus, provides a framework for prioritizing improvement measures (De Bruin et al., 2005; Iversen et al., 1999). Consequently, maturity models are suitable to support decision-making, for instance, in business process management (BPM) (Pöppelbuß et al., 2015), healthcare management (Cleven, Winter, Wortmann, & Mettler, 2014), corporate sustainability management (Müller & Pfleger, 2014), information technology (IT) management (Gottschalk, 2009), and knowledge management (Kulkarni & Freeze, 2004). In practice, numerous proprietary maturity models have been proposed by software companies and consultancies (Jacobson, 2016; Scott, Carvalho, D'Ambra, & Rutherford, 2001). The frequent use of maturity models can be explained by their various purposes of use. For instance, they can be used to assess a company's as-is situation, prioritize improvement measures, and control progress (Iversen, Nielsen, & Norbjerg, 1999) depending on the application of different stages of development or maturity regarding a distinct application domain (Müller & Pfleger, 2014; Tarhan, Turetken, & Reijers, 2016).

Maturity models are often criticized for their design or because of their usage as design artefacts (Pöppelbuß et al., 2015; Tarhan et al., 2016). Design-related criticism is rooted in the assumption of predefined maturation paths, lack of empirical foundations, or oversimplification of reality (De Bruin, Rosemann, Freeze, & Kulkarni, 2005; McCormack et al., 2009). Maturity models as design artefacts can be used for descriptive and prescriptive purposes (Röglinger, Pöppelbuß, & Becker, 2012; Tarhan et al., 2016). A variety of maturity models for descriptive purposes have been proposed to assess existing situations (Pöppelbuß, Niehaves, Simons, & Becker, 2011; Tarhan et al., 2016). These models are appropriate for determining the actual maturity levels of different capability areas with regard to specific company goals (Becker, Niehaves, Pöppelbuß, & Simons, 2010; Rosemann & De Bruin, 2005). According to design principles for the prescriptive purpose of use, maturity models must contain improvement measures for each maturity level as well as a decision calculus for prioritizing improvement measures (Pöppelbuß & Röglinger 2011). Despite these design principles, few maturity models can be applied for a prescriptive purpose of use (Forstner, Kamprath, & Röglinger, 2014; Tarhan et al., 2016). Most available maturity models define only maturity levels and recommend which capability areas should be developed, but they do not provide concrete guidance on the extent to which capability levels should be extended (Curtis & Alden, 2007; Pöppelbuß & Röglinger, 2011). Considerable research effort has been invested in addressing the criticism of maturity models (Tarhan et al., 2016). For instance, besides design principles for maturity models (Pöppelbuß & Röglinger, 2011), Lahrmann, Marx, Mettler, Winter, & Wortmann (2011) apply the Rasch algorithm to derive empirical documented maturity models. Forstner et al. (2014) propose a conceptual framework for structuring capability development decisions. The framework builds on process maturity models and the principles of value-based management (VBM). Forstner et al. (2014) take on a novel perspective on the development of multiple capability areas, as they consider the option of reducing maturity levels for cases in which this is sensible with regard to the goals of the company in focus. This framework, however, also has several shortcomings. For instance, interactions among capability areas are assumed to be symmetrically and the impact of each capability area on the company's goals as well as the interactions among capability areas are derived based on expert interviews and/or specifications from the capability maturity model integration (CMMI) (Forstner et al., 2014). With these assumptions and because of a missing quantitative determination of the interactions among capability areas, the model oversimplifies reality and, thus, does not tap its full potential.

The preceding analysis reveals the following research gaps. First, there are many maturity models for descriptive purposes to determine the company's as-is situation, but there is a lack of models for prescriptive purposes of use that help prioritize improvement measures. Thus, concrete guidance on which capability area should be developed and to what extent is missing. Second, existing maturity models are often criticized for their assumptions, especially that all interactions among capability areas are symmetrically or that these interactions evaluated subjectively via expert interviews and not via methods of prescriptive decision theory. Thus, we investigate the following research question: *How can maturity models be enhanced for prescriptive purpose of use considering the importance of capability areas as well as the impact of interactions among these capability areas?*

To address this research question, we propose a methodological extension of maturity models. With this extension, existing maturity models can be enhanced such that they explicitly account for the importance of multiple capability areas and consider the impact of interactions among capability areas. Consequently, the importance of each capability area can be determined using a multi-criteria approach. To do so, we apply an error-adjusted Analytical Hierarchy Process (AHP) approach (Tomashevskii, 2015) to determine the relative importance of capability areas. The AHP is a utility-based multi-criteria decision-making (MCDM) method and appropriate to answer the first part of the research question (Polatidis, Haralambopoulos, Munda, & Vreeker, 2006). Second, we adjust parts of the Google PageRank (Langville & Meyer, 2011) to receive weights for the interactions among capability areas. This is reasonable, as the PageRank is a method to determine dependencies in networks and to calculate centrality ratings (Lehnert, Röglinger, Seyfried, & Siegert, 2015).

Consequently, our methodological extension has three main contributions: First, we enhance maturity models for a prescriptive purpose of use and resolve simplifying assumptions of extant maturity models and decision frameworks based on maturity models. Second, to the best of our knowledge, our extension is the first application of the error estimation to the entire AHP method (Tomashevskii, 2015). Third, to answer our research question, we combine methods from both multi-criteria decision-making, i.e., the error-adjusted AHP, and network analysis, i.e., the Google PageRank.

The rest of the paper is organized as follows. In Section 2, we justify the use of maturity models in general, provide the CMMI blueprint for maturity models, and sketch the decision framework as per Forstner et al. (2014), on which we build our work. This framework is suitable to demonstrate the methodological extension, as it builds on the CMMI blueprint and nomenclature, which is a quasi-standard for most maturity models. In Section 3, we introduce the methodological extension for maturity models. In Section 4, we report the results of an application example based on Röglinger and Kamprath (2012). This is reasonable, as Forstner et al. (2014) refer to the same example as they build up on the work of Röglinger and Kamprath

(2012). We conclude in Section 5 by reviewing key results, discussing the study's limitations, and pointing to future research possibilities.

2 Background – Foundations of Maturity Models

Based on the assumption of predictable patterns of organizational evolution and change, maturity models typically represent theories about how an organization's capabilities evolve along an anticipated, desired, or logical path of predefined stages (Pöppelbuß et al., 2011; Van de Ven & Poole, 1995). Consequently, maturity models are also termed stages-of-growth models, stage models, or stage theories (Prananto, McKay, & Marshall, 2003). The main purpose of maturity models is to outline the stages of maturation paths (Röglinger et al., 2012). Applying these stages enables an evaluation of an organization's capabilities with regard to a certain discipline or company goal, and thus, provides a framework for prioritizing improvement measures that are meaningful to the organization (De Bruin et al., 2005; Iversen et al., 1999). To do so, maturity models typically contain capability areas, which are also referred to as areas, enablers, or process areas in the domain of BPM (Hammer, 2007; Weber, Curtis, & Gardiner, 2008). Each capability area has a capability level that expresses the extent to which that area is developed (institutionalized), that is, how predictably and consistently the results of the underlying processes are achieved (Rosemann & De Bruin, 2005; Van Looy et al., 2011). Different capability levels can be aggregated to a maturity level, as shown in Figure 1. Figure 1 uses the nomenclature of the CMMI blueprint, which is a quasi-standard for most maturity models (Software Engineering Institute, 2009). Maturity models can be applied to different purposes of use, that is, to assess the as-is situation, prioritize improvement measures, and control progress (Iversen et al., 1999). Maturity models for descriptive purposes of use can be applied to as-is assessments (De Bruin et al., 2005). A maturity model serves a prescriptive purpose of use if it indicates how to identify desirable future capability levels and provides guidance on how to prioritize improvement measures (Röglinger et al., 2012; Tarhan et al., 2016). Finally, a maturity model serves comparative purposes of use if it allows for internal and external benchmarking (De Bruin et al., 2005).

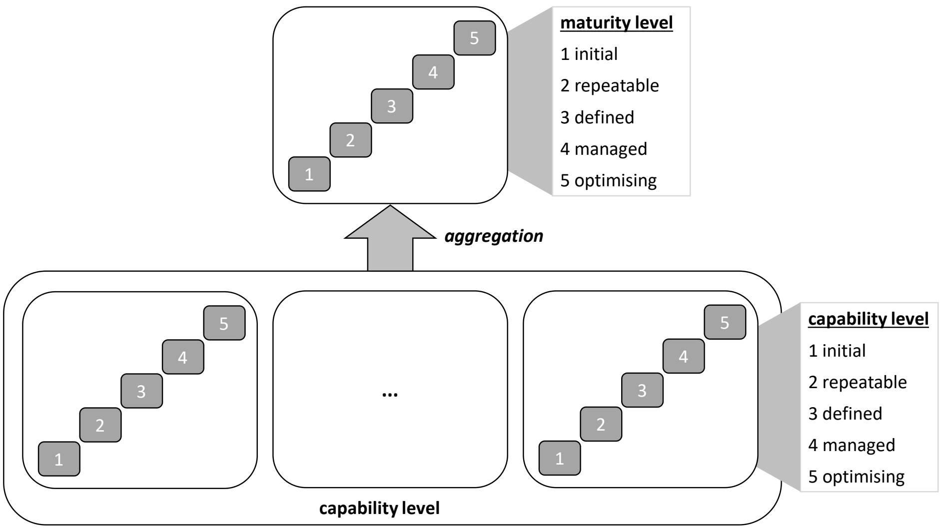

Figure 1. Aggregation of capability levels to a maturity level

The most popular maturity models are those belonging to the CMMI family, which was initially designed for software development (Paulk, Curtis, Chrissis, & Weber, 1993). Using the CMMI blueprint, more than 150 maturity models have been proposed (De Bruin et al., 2005). Based on CMMI, multiple constellations have been established, for example, the CMMI for services, CMMI for development, CMMI for acquisition, and people CMMI (Software Engineering Institute, 2009). All CMMI constellations have the same structure and core components (Chrissis, Konrad, & Shrum, 2011). In addition, CMMI maturity models are used in IT management, knowledge management, and project management, to name just a few application domains (Software Engineering Institute, 2009). The CMMI models, in general, enable two different improvement modes. In continuous representation, capability development starts at the capability area level. An organization selects capability areas and implements predefined improvement measures to a desired extent. Following the staged representation, capability development focuses on maturity and is driven top-down from the organizational layer. The idea is to implement improvement measures of previously defined capability areas according to rules predefined in CMMI (Forstner et al. 2014). Consequently, the CMMI blueprint is suitable as a basis for the development of maturity models with a prescriptive purpose of use.

A decision framework, based on the CMMI blueprint, that extends maturity models for prescriptive purposes is the framework proposed by Forstner et al. (2014). Their decision framework aims to structure capability development decisions, as the authors investigate capability development decisions based on process maturity models and analyse which capability level increases or reductions affect the highest value contribution (Forstner et al., 2014). For this purpose, the decision framework builds on the principles of VBM, which is closely related to investment theory, and adopts CMMI's continuous representation. An overarching valuation paradigm, such as VBM, is needed to balance different goals, as goals can be competing. The aim is to identify the optimal trade-off among company goals for decision-making purposes. At this point, VBM aims to sustainably increase an organization's firm value from a long-term perspective (Ittner & Larcker, 2001; Koller, Goedhart, & Wessels, 2010). For VBM to be fully realized, all corporate activities, including capability development decisions, must be aligned with the objective of maximizing the firm value (Lehnert, Linhart, & Röglinger, 2016). Accordingly, Forstner et al. (2014) use a cash flow-related valuation function depending on the change of the overall maturity level and thus, on the changes in each capability level. Depending on the concrete context and company goals, the decision framework can be applied by using any function depending on the changes of the maturity and capability levels. Thus, this decision framework is widely applicable.

Because of the usage of the CMMI blueprint, we use the framework of Forstner et al. (2014) as a reference point to specify our methodological extension. In addition, it is reasonable to enhance this decision framework, which, to the best of our knowledge, is the only approach that extends maturity models for prescriptive purposes. However, as already demonstrated, this decision framework does not tap its full potential. Consequently, we abstract from CMMI peculiarities and the used nomenclature from this decision framework wherever reasonable. The methodological extension itself can be applied to several maturity models.

3 Extended Decision Framework

In this section, we propose a methodological extension that can be applied to several maturity models and that enhances the decision framework proposed by Forstner et al. (2014). With this extension, existing maturity models can be enhanced for prescriptive purposes in such a way that they account for the importance of multiple capability areas and consider the impact of interactions among capability areas, while the importance of each capability area can be calculated using a multi-criteria approach. So far, all interactions among capability areas are assumed to be symmetrically and the impact of each capability area as well as the interactions among these areas are derived via expert interviews and/or specifications from CMMI (Forstner et al., 2014). This is problematic, as a decision maker can make pairwise comparisons of alternatives with respect to one criteria, but if the number of criteria or alternatives increases, it is not possible to grasp the big picture (Saaty, 1980). For cases with more than two criteria, this becomes a difficult or almost impossible task, as a decision maker generates his or her ranking via transitivity (Saaty, 1980). In particular, for cases with multiple competing company goals, the methods frequently used fail.

To solve this problem, our methodological extension is organized based on the following four sections. In section 3.1, we provide the basic model and nomenclature to create the basis for the methodological extension. In section 3.2, we present a quantitative method to determine the relative importance of a distinct capability area with regard to multiple company goals. To do so, we adopt an extended AHP approach to determine the importance of a distinct capability area (Tomashevskii, 2015). In section 3.3, we determine the interactions among different capability areas, using components of the Google PageRank algorithm (Langville & Meyer, 2011). This is reasonable, as these interactions are also relevant for capability decision-making purposes (Lehnert et al., 2015). Finally, in section 3.4, the results of both methods are scaled and aggregated into a matrix in such a way that the results are comparable to each other.

3.1 Basic Model

Our methodological extension builds on Forstner et al. (2014), who propose a decision framework for prescriptive purposes in the domain of BPM. The basic idea of the decision framework is the distinction of two layers, as shown in Figure 2. The company level contains a company's overall maturity level, that is, the aggregation of multiple capability areas, and the company's goals that are relevant for decision-making, for example, allowing more service customization possibilities for customers or sustainably increasing the long-term firm value. In addition, a company comprises multiple capability areas, which are intended to contribute toward achieving the company's goals. At this point, not all capability areas are relevant for decision-making. Those capability areas p_i that are considered in the maturity model are already developed to a specific capability level, l_i. The total number of capability areas is restricted to $n \in \mathbb{N}$ and the aggregation of all capability levels at the company level is called maturity level, m. Each capability area influences the company level, that is, the achievement of the company's goals, more or less. The relative importance of a distinct capability area is expressed by factor $s_{ii} \in S$ (Huang & Han, 2006). In addition, the capability areas can influence each other. This means that strengthening or weakening a capability area can influence another capability area. These interactions are characterized by factor $s_{ij} \in S$, which can be interpreted as the strength of the influence from capability area p_i on capability area p_j, for $i \neq j$. In contrast to Forstner et al. (2014), we assume that the interactions among two capability areas are not symmetric. This is reasonable, as interactions among two capability areas are not necessarily symmetric, that is, the influence of capability area p_i on p_j is greater than vice versa.

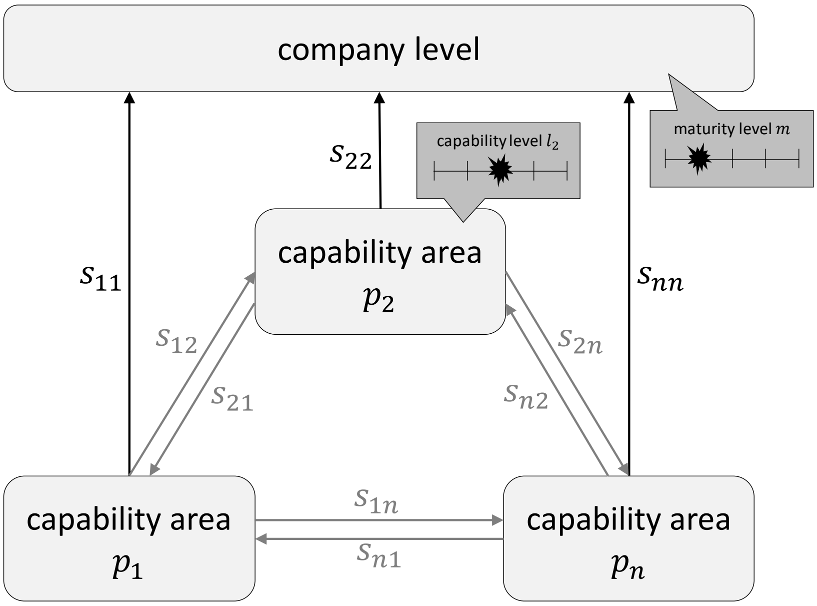

Figure 2. Influence of capability areas on company level and interactions among capability areas

To approximate the current maturity level of the company, we consider an objective function which essentially depends on the set of all capability levels L, as well as on the set of pairwise relations among all capability areas S. Consequently, the function, representing the aggregation of the capability levels, is denoted by $m \coloneqq f(L, S)$. Changes of the overall maturity level, $\Delta m \in \mathbb{R}_{\geq 0}$, are defined by changes in the capability levels Δl_i in the aggregation function $\Delta m = \Delta f(L, S) = f(\Delta L, S)$. According to Forstner et al. 2014, we assume, that $\Delta f : \Delta L \times S \to \mathbb{R}_{\geq 0}$ is linear and defined as shown in Eq. (1).

$$\Delta m = f(\Delta L, S) = \sum_{i,j=1}^{n} \Delta l_i \cdot s_{ij} = \sum_{i=1}^{n} \Delta l_i \cdot s_{ii} + \sum_{\substack{i,j=1 \\ i \neq j}}^{n} \Delta l_i \cdot s_{ij} \tag{1}$$

$$\text{with } s_{ii} \in \mathbb{R}_{>0} \text{ and } s_{ij} \in \mathbb{R}_{\geq 0}$$

3.2 Importance of a Distinct Capability Area

To determine the relative importance of a distinct capability area, a weighting or ranking of the capability areas, that is, a method to determine the values, s_{ii}, is needed. At this point, especially for cases with multiple competing company goals, the methods frequently used fail. Some MCDM methods deal with this issue and help rank different alternatives with regard to predefined criteria. Two established MCDM methods are the preference ranking organization method for enrichment evaluation (PROMETHEE) (Brans & Vincke, 1985) and the AHP (Saaty, 1977, 1980). Both methods are used very frequently for many application domains (Behzadian, Kazemzadeh, Albadvi, & Aghdasi, 2009; Vaidya & Kumar, 2006). PROMETHEE belongs to the class of outranking methods, whereas AHP is a utility-based MCDM method (Polatidis et al., 2006). Methods from the outranking class compare the alternatives criteriawise. Thus, a strong value in just one criteria makes it likely to outperform and thereby outrank other alternatives (Polatidis et al., 2006). By contrast, utility-based MCDM translates the values of all criteria according to one measure into comparable values, for example, by applying a utility function or through a predefined scale. Consequently, the criteria are chosen to fit to the company goals. Considering this, it is reasonable to select a utility-based MCDM method to answer our research question. It is challenging to choose the best method, since every MCDM method has its shortcomings. We use the AHP as it can answer the first part of the research question (Polatidis et al., 2006). To address the main criticism on AHP (Smith & Von Winterfeldt, 2004; Bana e Costa & Vansnick, 2008), we apply a recently proposed error-adjusted AHP (Tomashevskii, 2015).

3.2.1 Analytical Hierarchy Process

We apply AHP in three steps, which are based on the four AHP axioms (Saaty, 1986). In the first step, we must identify criteria relevant for the company goals and the capability areas under investigation. In the AHP nomenclature, capability areas represent the alternatives. Then, the decision problem has to be decomposed into a hierarchy, comprising a finite number of layers. The first layer consists of criteria, which can be, for example, performance measures, like time, costs, and any possible factor that is relevant for evaluating a capability area with regard to the company goals. Each criterion might be subdivided (e.g. time into waiting and processing time) in a way, that each subdivision on layer k opens a new $(k+1)$th layer below its parent criterion in the hierarchy. Considering this, we denote a criterion as $c_{j_1,\dots,j_k}^{(k)}$, where k denotes the layer of the criterion, and the set $j_1, \dots, j_k \in \mathbb{N}$ regards possible subdivisions. For example, the criterion time in layer one $c_1^{(1)}$ can be split into waiting time $c_{1,1}^{(2)}$ and processing time $c_{1,2}^{(2)}$. Finally, at the last hierarchy layer, all capability areas l_i are listed. Consequently, the hierarchy consists of different paths, that is, a distinct set of connections between different layers from the company goal up to the capability areas. The number of relevant subdivisions plus one expresses the length of a distinct path, since the last criterion is always connected with a capability area. The number of hierarchy layers is denoted by $n_a \in \mathbb{N}$.

Table 1. Scale of relative importance of pairwise comparisons (e.g. Saaty, 1986)

Relative importance according to the companys'goal, c_{ij}	Definition	Explanation
1	Equal importance	Two process areas contribute equally to the company goals.
3	Moderate importance of one over another	Experience and judgment slightly favour one process area over another.
5	Essential or strong importance	Experience and judgment strongly favour one process area over another.
7	Demonstrated importance	A process area is strongly favoured and its dominance is demonstrated in practice.

9	Extreme importance	The evidence favouring one process area over another is of the highest possible order of affirmation.
2,4,6,8	Intermediate values between two adjacent judgments	When compromise is needed.

In the second step, comparative judgments between the hierarchy layers have to be made. All criteria in layer $k = 1$ are compared with respect to the company goals. This comparison is aggregated in a comparison matrix, $C_1^{(1)} \in \mathbb{R}^{n \times n}$, $n \in \mathbb{N}$. In addition, all sublayers are compared with respect to their parent element from the next upper level. The result is comparison matrix $C_{j_1,\dots,j_{k-1}}^{(k)} \in \mathbb{R}^{n(k) \times n(k)}$, $n(k) \in \mathbb{N}$ for each layer k. For example, again we consider waiting time $c_{1,1}^{(2)}$ and processing time $c_{1,2}^{(2)}$. Being compared with each other with respect to criterion time $c_1^{(1)}$, they form comparison matrix $C_1^{(2)}$. Consequently, several comparison matrices can exist for one sublayer. Finally, each capability area l_i is compared with respect to each criterion. If additional sub-criteria exist, then these replace their parent criteria in the upper layer(s). All comparisons can be made using the Saaty scale (Saaty, 1977). The scales for the pairwise comparisons are shown in Table 1. In addition, the comparison matrices $C^{(k)}$ must be reciprocal, that is, for all entries, $c_{ij} = \frac{1}{c_{ji}}$ must apply. Next, for each comparison matrix $C^{(k)}$, the principal eigenvector $x^{(k)}$ is calculated (Saaty, 2003) with respect to the maximal eigenvalue $\lambda_{\max}^{(k)}$. The relation of these factors is shown in Eq. (2).

$$C^{(k)} x^{(k)} = \lambda_{\max}^{(k)} x^{(k)} \tag{2}$$

In the third and final step, all principal eigenvectors are synthesized by aggregation, which adds up for each capability area the respective importance of each (sub-)criterion multiplied by the relative importance to the next upper hierarchy level(s) until the highest hierarchy level is reached. To describe this aggregation in a general manner a multi-index is introduced. This multi-index $\mathfrak{J} = \{j_1, j_2, \dots, j_{n_a}\}$, with $n_a \in \mathbb{N}_{\geq 2}$, expresses the different paths within the hierarchy. At this point, J is a distinct representative of $\mathfrak{J}$, that is, $J = j_1 j_2 \dots j_{n_a}$ with fixed $j_1 \dots j_{n_a}$. A representative $J_k = j_1 j_2 \dots j_k \in \mathfrak{J}_k \subset \mathfrak{J}$, for $k \leq n_a$, has fixed values up to layer k. The k-th entry of the representative $J(k) = j_k \in [0, \dots, n_{J(k)}]$, for $n_k \in \mathbb{N}$, adds up the subdivisions of the criterion with the index J_{k-1}. Consequently, n_k reflects the subdivisions of $c_{J_{k-1}}$. If a criterion only has sub-criteria up to the k-th hierarchy layer, then applies $n_{J(k+1)} = n_{J(k+2)} = \dots = n_a = 0$. With this index notation, the eigenvector regarding the maximal eigenvalue of $C_{J_{k-1}}^{(k)}$ is expressed by $x_{J_{k-1}}^{(k)}$ where applies $x_{J_0}^{(1)} = x^{(1)}$ for the case $k = 1$. The components are denoted by $x_{J_{k-1},l}^{(k)}$ for $l \in 1, \dots, ran\left(C_J^{(k)}\right) = n_{J(k)}$. Each aggregation (shown in Eq. (3)) enters into the overall preference vector $\tilde{r} \in \mathbb{R}^n$. These values of the final preference vector represent the rank of the considered capability areas.

$$\tilde{r}_i = \sum_{j_1=1}^{n_{J(1)}} x_{,j_1}^{(1)} \cdot \chi_{J_1}^{(2)}$$

$$\text{for } i \in 1, \dots, n_a \text{ with}$$

$$\chi_{J_{k-1}}^{(k)} = \begin{cases} \sum_{h_k=1}^{n_{H(k)}} x_{H_{k-1},h_k}^{(k)} \cdot \chi_{H_k}^{(k+1)} & \text{for } H_{k-1} = J_{k-1} \text{ and } n_{H(k)} \neq 0 \\ x_{H_{n_a},i}^{(n_a)} & \text{for } k = n_a \text{ or } n_{H(k)} = 0 \\ 0 & \text{for } H_{k-1} \neq J_{k-1} \end{cases} \tag{3}$$

3.2.2 *Dealing with Criticism of Analytical Hierarchy Process*

The main criticism of the AHP deals with the interpretation of the preference vector, that is, with the ranking of the alternatives or capability areas in our context. First, the results are criticized for being instable, as adding or removing criteria leads in some cases to rank reversals between the original and remaining criteria (Belton & Grear, 1985). Second, the preference order of the decision maker can be violated. In other words, the decision maker weights criteria c_i as more important than c_j, but the respective weights results in the reverse, that is, $r(c_j)$ is more important than $r(c_i)$ (Bana e Costa & Vansnick, 2008). Third, in some cases, a reformulation of the problem (scale inversion) leads to rank reversals (Johnson, Beine, & Wang, 1979). In addition, the interpretation of the results can be difficult, if the ranks of two alternatives are very close to each other. The prevailing opinion is that rank reversals and instabilities appear because of inconsistencies or the violation of transitivity ($c_{ij} \cdot c_{jk} = c_{ik}$), which appears through the construction of the comparison matrices (Tomashevskii, 2015). Saaty (1980) introduces a consistency ratio (CR) to measure the violation of this inconsistency. According to his reasoning, a comparison matrix with $CR < 0.1$ is consistent. Thus, rank reversals can still appear for $CR < 0.1$ and Tomashevskii (2015) shows that CR is an inappropriate error indicator. In addition, a rising rank of the considered comparison matrix weakens the results further. Tomashevskii (2015) introduces a measure to approximate the error caused by the violation of inconsistency. The measure for comparison matrix $C^{(k)} = \left(c_{ij}^{(k)}\right)_{\{i,j\} \in [1,\dots,n]}$ and the respective principal eigenvector $x^{(k)} \in \mathbb{R}^n$ is shown in Eq. (4).

$$\Delta x_i^{(k)} = \pm\sqrt{\frac{1}{n-1} \sum_{b=1}^{n} \left(\frac{n}{\lambda_{max}} c_{ib}^{(k)} x_b^{(k)} - x_i\right)^2}\ , i = 1, \dots, n \tag{4}$$

As this error, $\Delta x^{(k)} \in \mathbb{R}^{n(k)}$ belongs to the *k*th comparison matrix, we estimate the error term for the whole AHP, that is, for all comparison matrices and through the aggregation step. This is an innovation, as the error term never before has been applied to the whole AHP method. We use the standard Gaussian error approximation to obtain the overall preference vector $\tilde{r}$ completed with the error term $\pm\Delta\tilde{r}$, shown in Eq. (5). An application of this equation is shown in Eq. (12).

$$\Delta\tilde{r}_i = \sum\nolimits_{\{eigenvalues\}} \frac{\tilde{\partial}\tilde{r}_i}{\partial x_{J_{k-1}}^{(k)}} \cdot \Delta x_{J_{k-1}}^{(k)} \tag{5}$$

$$\left|\Delta\tilde{r}_i + \Delta\tilde{r}_j\right| < |\tilde{r}_i - \tilde{r}_j| \tag{6}$$

Our aim is to determine an error-adjusted preference vector, r. For this purpose, we propose a stepwise procedure. Essentially, we use the results of Eq. (3), the overall preference vector, $\tilde{r}$, and the results of Eq. (5), the error term $\Delta\tilde{r}$. These terms are used in the condition, shown in Eq. (6). If this condition is already violated by one of the eigenvalues x, the entries in the comparison matrices have to be checked for plausibility and changed if necessary (Kulakowski, 2015). If the condition is not violated by any eigenvalue, the overall preference vector, $\tilde{r}$, and its error term, $\Delta\tilde{r}$, are compared. If the condition holds, the decision maker is not indifferent with regard to any capability area and thus, the overall preference vector is also the error-adjusted preference vector $\tilde{r} = r$. If Eq. (6) is violated for $\tilde{r}$ and the entries in the comparison matrices turn out to be plausible, the decision maker is indifferent between these alternatives, that is, capability areas. A violation of Eq. (6) implies that the error intervals of at least two capability areas overlap. In addition, in cases with small overlaps, in which a rank reversal seems unlikely to appear, we suggest redefining the entries under consideration in the preference vector. For each set of entries F in the preference vector $\tilde{r}$ for which the decision maker is indifferent, according to Eq. (6), a refinement is necessary according to Eq. (7).

$$r_i := \frac{\sum_{i \in F} \tilde{r}_i}{|F|} \tag{7}$$

for all $i \in F$, where F is the quantity of indifferent entries in r

For all other entries, $r_i := \tilde{r}_i$ applies. The resulting vector r is the error-adjusted preference vector, which is still normed. For example, in a case in which $\tilde{r}_1, \tilde{r}_2$, and $\tilde{r}_5$ overlap according to Eq. (6), the quantity includes three entries $|F| = 3$ and the entries in the error-adjusted preference vector are according to Eq. (7) $r_i = \frac{\tilde{r}_1 + \tilde{r}_2 + \tilde{r}_5}{3}$ for $i \in \{1; 2; 5\}$. For further overlapping entries, the procedure has to be repeated. In section 3.4, we adjust the scaling of the error-adjusted preference vector and convert r_i into s_{ii} in order to create a scaled synergy matrix $S = \left(s_{ij}\right)$. This is necessary to compare all entries within the synergy matrix, which is the overall result of the methodological extension.

3.3 Interactions among Capability Areas

To determine the relative importance of the interactions among capability areas, a weighting or ranking of these relations, that is, a method to determine values s_{ij}, is needed. This is reasonable, as capability areas are often connected to some extent, or potentially influence each other (Forstner et al., 2014). Many types of interactions are described in the literature. In BPM research, different relationships are descripted by Dijkman, Vanderfeesten, and Reijers (2016). It is crucial to account for these interactions among capability areas, especially when planning the improvement of multiple capability areas (Lehnert et al., 2015). Few quantitative approaches in the domain of capability development explicitly consider interactions or dependencies between different process areas or processes (Lehnert et al., 2015; Malinova, Leopold, & Mendling, 2014). Lehnert et al. (2015) apply process landscapes and the Google

PageRank algorithm (Brin & Page, 1998; Langville & Meyer, 2011) to evaluate dependencies among processes in order to identify the process with the highest influence on other processes with the aim of prioritizing improvement initiatives. To answer particular aspects of our research question, we apply and adjust the PageRank algorithm to receive weights for the interactions among capability areas (Langville & Meyer, 2011).

We apply only parts of the algorithm, as at this point, the interactions among capability areas are of special interest, not identification of the most important capability area in the whole network. This is reasonable, as we propose a method in section 3.2 to determine the importance of a distinct capability area with regard to multiple company goals. To apply the PageRank algorithm and network approach, we denote capability areas as nodes and the interactions between them as edges. Furthermore, the edges can have weights and are directed, which is represented by the number of capability areas that are connected through a use relationship. This is reasonable, as interactions among two capability areas or edges are not necessarily symmetric, that is, the influence of capability areas p_j on p_i can be greater than vice versa. In this context, each interaction among capability areas is recognized as a movement along the respective edges between two involved capability areas. Consequently, the overall network is described by an adjacency matrix, $W \in \mathbb{R}^{n \times n}$, where element $w_{ji} \in [0,1]$ represents the weight of the link that points from capability areas p_j to p_i. The original PageRank algorithm includes parameter $d \in [0,1]$, which indicates the fraction of the PageRank that stems from the network structure. In our application context, this parameter balances the effects of the interactions between edges and the network structure on the resulting PageRank $PR(i)$, that is, the ranking of capability area p_i. Consequently, the higher the parameter d (dampening factor) is, the lower is the proportion of effects between process areas that are not considered by the network. When ranking web pages, the original application context of PageRank d is typically set to 0.85 (Langville & Meyer, 2011). With these assumptions, the weighted PageRank of each capability area p_i can be determined using Eq. (8) (Langville & Meyer, 2011).

$$PR(i) = \frac{(1-d)}{n} + d \cdot \sum\nolimits_{j \in I_i}^{n} \frac{PR(j) \cdot w_{ji}}{\sum_{k \in O_j} w_{jk}} \tag{8}$$

where I_i is the set of capability areas pointing to capability area p_i

and the O_j is the set of capability areas that depended on capability area p_i

For more details on the PageRank algorithm, we refer to the literature (e.g. Langville & Meyer, 2011). Because our aim is to determine the importance of the interaction between capability areas p_i and p_j, we decompose the PageRank according to Eq. (9), through which the directed interactions s_{ij} among two capability areas can be determined. Consequently, s_{ij} expresses the influence of capability areas p_i on p_j. A higher value of s_{ij} means a stronger interaction among the capability areas, where interaction means correlation with regard to capability improvement.

$$s_{ij} = \frac{(1-d)}{n^2} + d \cdot \frac{PR(j) \cdot w_{ji}}{\sum_{k \in O_j} w_{jk}} \cdot \chi_{j \in I_i} \tag{9}$$

where $\chi_{j \in I_i} = \begin{cases} 1, \text{if } j \in I_i \\ 0, \text{else} \end{cases}$, such that $PR(i) = \sum_{j=1}^{n} s_{ij}$

The results are shifted by a constant factor $\frac{(1-d)}{n^2}$, which is in principle not relevant for the interpretation of all interactions among capability areas, as the factor is constant for all interactions. This factor can be interpreted as the minimum influence between two capability areas depending on parameter d. The shift is relevant to satisfy convergence issues related to the PageRank algorithm. Consequently, a method is applied to determine values s_{ij}, that is, the relative importance of the interactions among different capability areas.

3.4 Merging the Results into a Scaled Matrix

The aim of the proposed methodological extension is to set up the synergy matrix $S = (s_{ij})$, that is, the coefficients used in Eq. (1). To do so, in section 3.2, we provide a quantitative method to determine the error-adjusted preference vector r_i, that is, the relative importance of a distinct capability area using an enhanced AHP. In section 3.3, we determine s_{ij}, namely, the interactions among different capability areas, using parts of the PageRank algorithm. The results of both methods are aggregated and transformed to create the matrix $S = (s_{ij})$ so as to be able to compare all entries within the matrix. The values of r_i are normalized with respect to each other. In addition, the values S_{ij} are normalized with respect to each other, but in general, r_i and S_{ij} are not directly comparable. The dimensionless values of r_i and s_{ij} decrease with a rising number of considered capability areas, as $\sum_{i=1}^{n} r_i = 1$ and $\sum_{i=1}^{n} \sum_{j=1}^{n} s_{ij} = 1$ hold for any $n \in \mathbb{N}$. However, the values r_i determined using the error-adjusted AHP decrease proportional to $\frac{1}{n}$, at which the values s_{ij} determined with the PageRank algorithm decrease proportional to $\frac{1}{n^2}$. In other words, a simple merge of the values into a matrix would lead to an overweighting of r_i. Consequently, it is reasonable to scale all coefficients accordingly to enable comparisons. As $r_i \sim \frac{1}{n}$ and $s_{ij} \sim \frac{1}{n^2}$ hold, we show a corresponding scaling in Eq. (10).

$$s_{ii} := \frac{r_i}{n} \sim \frac{1}{n^2}\ ;\ s_{ij} \sim \frac{1}{n^2} \quad \text{for all } i, j \in [1, \dots, n] \tag{10}$$

Because of the scaling, all results are in the same order of magnitude and independent of n. Consequently, all entries in the synergy matrix $S = (s_{ij})$ are comparable. The synergy matrix can be used in any objective function respecting the influence of changes in the capability levels to identify an appropriate constellation of capability levels by maximizing this function.

4 Application Example

In this section, we report the results of an application example based on prior work of Röglinger and Kamprath (2012). The example demonstrates the application of the entire methodological extension in a concrete usage context. The first step to apply the methodological extension is the selection of an appropriate maturity model and the definition of relevant company goals for decision-making. Depending on the context at hand, the company goals are only relevant for a specific business unit in focus up to the entire company as the methodological extension can be applied to a part of the company or the entire company. The company goals can be defined by the management or other relevant stakeholders. Second, all criteria relevant for the company goals must be defined and operationalized. At this point, the most appropriate criteria to measure goal achievement depend on the company goals and on the company at hand. Third, relevant capability areas must be defined using information both from the management and information contained in the used maturity model. Some maturity models contain very detailed descriptions of capability areas and information about potential dependences to other capability areas that are very helpful at this point (CMMI Product Team, 2010).

In this application example, we consider a fictitious IT service provider. The proposed maturity model is based on the CMMI for services (CMMI-SVC) process maturity model (CMMI Product Team, 2010), since it is a good fit for the needs of service providers (Becker et al., 2010). Capability areas are referred to as process areas in this usage context. The service provider follows the company goal to allow more service customization possibilities for customers. Consequently, service customization means more flexibility for the customer concerning service composition. In addition, the service provider follows the principles of VBM and thus, aims to sustainably increase its long-term firm value (Koller et al., 2010). In their application example, Röglinger and Kamprath (2012) assume that all process areas are equally weighted. Thus, we have to define relevant criteria for the service provider ourselves. At this point, we assume that the criteria c_1: *time* and c_2: *flexibility* are relevant for the company goal. As there are multiple ways to operationalize flexibility (Sethi & Sethi, 1990), we assume that the service provider is particularly interested in c_{2_1}: *design flexibility* and c_{2_2}: *flexibility to change* (Schonenberg, Mans, Russell, Mulyar, & Van der Aalst, 2008). The alternatives, that is, the process areas, are taken from the CMMI-SVC. In this application example, we consider four process areas: p_1–p_4. The first is *incident resolution and prevention* (IRP), that is, the handling of errors and incidents in the running business and its prevention. The second process area is *service delivery* (SD), since the financial and service level agreement planning is a very sensitive topic to allow more customization. The third process area, *organizational process performance* (OPP), and the fourth process area, *requirements management* (RM), are also included in the demonstration example. All four process areas are relevant for the company goal. Consequently, the question is how to improve the capability levels of the considered process areas. As already stated, we apply our methodological extension in this context to derive the synergy matrix $S = \left(s_{ij}\right)_{i,j\in\{1,\dots,n\}}$, which represents the relative importance of all process areas and the interactions among the process areas.

4.1 Relative Importance of Process Areas

To apply the first part of our methodological extension, that is, to determine the relative importance of the process areas, we rank all considered process areas p_1–p_4. To determine a ranking of the process areas, we apply the error-adjusted AHP, as presented in section 3.2. The first step is to decompose the criteria (i.e. c_1 and c_2) and sub-criteria (i.e. c_{2_1} and c_{2_2}) into a hierarchy, as shown in Figure 3.

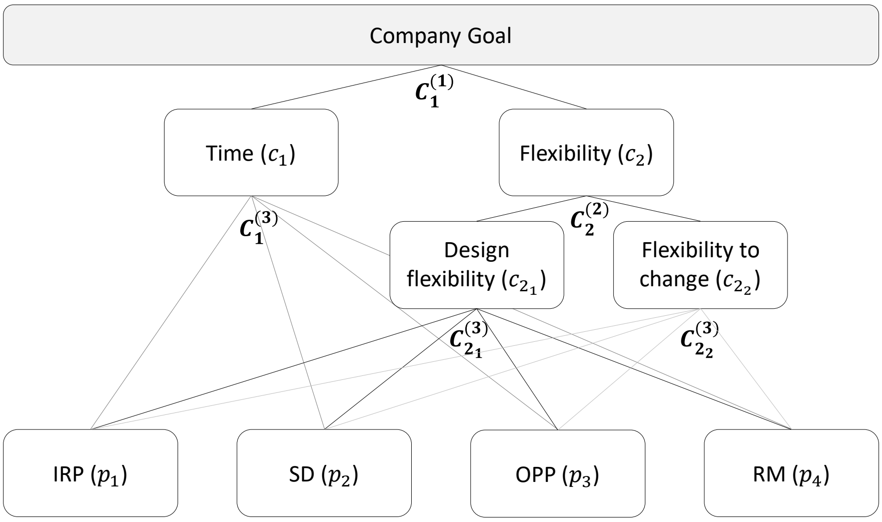

Figure 3. Hierarchy for the application of AHP in the application example

Figure 3 contains all comparison matrices $C^{(k)}_{j_1,\ldots,j_k \in \mathbb{N}}$. We determine these comparison matrices ourselves, according to the Saaty scale (Table 1). The pairwise comparisons on the first layer, that is, between criteria c_1 and c_2 with respect to the company goal are contained in matrix $C_1^{(1)}$. As some maturity models contain detailed descriptions of capability areas and information about potential dependencies among capability areas (e.g. CMMI Product Team, 2010), this information can be used as foundation for pairwise comparison. In the application example, we consider only one company goal, namely service customization. For cases with more than one company goal, the procedure is repeated for each goal. On the second layer, we compare sub-criteria c_{2_1} and c_{2_2} with regard to criterion c_2. The result of this comparison is the matrix $C_2^{(2)}$. Finally, we compare each process area p_1–p_4 with regard to sub-criteria c_{2_1} and c_{2_2} as well as to criterion c_1. These comparative results are covered by the corresponding matrices $C_{2_1}^{(3)}$, $C_{2_2}^{(3)}$, and $C_1^{(3)}$, which are included in Table 2. After the first step, we calculate the maximum eigenvalues for each comparison matrix and the corresponding eigenvectors x, according to Eq. (2). In addition, we calculate the error term for each eigenvector using Eq. (4). For each process area p_i, we can then calculate the corresponding entry $\tilde{r}_i$ for the preference vector using Eq. (11), which is an application of Eq. (3).

$$\tilde{r}_i = x_{1,1}^{(1)} \cdot x_{1,i}^{(3)} + \left(x_{1,2}^{(1)} \cdot x_{2,1}^{(2)}\right) \cdot x_{2_1,i}^{(3)} + \left(x_{1,2}^{(1)} \cdot x_{2,2}^{(2)}\right) \cdot x_{2_2,i}^{(3)} \tag{11}$$

To check whether rank reveals are likely to appear and to ensure stable ranking results, we first determine the error term $\Delta\,\tilde{r}_i$ for each process area p_i, as shown in Eq. (12), which is an application of Eq. (5). To do so, we calculate the error for each eigenvector according to Eq. (4). The corresponding results are shown in Table 2.

$$\begin{aligned}\Delta\,\tilde{r}_i &= \Delta x_{1,1}^{(1)} \cdot x_{1,i}^{(3)} + x_{1,1}^{(1)} \cdot \Delta x_{1,i}^{(3)} \\ &+\left(\Delta x_{1,2}^{(1)} \cdot x_{2,1}^{(2)}\right) \cdot x_{2_1,i}^{(3)} + \left(x_{1,2}^{(1)} \cdot \Delta x_{2,1}^{(2)}\right) \cdot x_{2_1,i}^{(3)} + \left(x_{1,2}^{(1)} \cdot x_{2,1}^{(2)}\right) \cdot \Delta x_{2_1,i}^{(3)}\end{aligned} \tag{12}$$

$$+\left(\Delta\, x_{1,2}^{(1)} \cdot x_{2,2}^{(2)}\right) \cdot x_{2_2,i}^{(3)} + \left(x_{1,2}^{(1)} \cdot \Delta x_{2,2}^{(2)}\right) \cdot x_{2_2,i}^{(3)} + \left(x_{1,2}^{(1)} \cdot x_{2,2}^{(2)}\right) \cdot \Delta\, x_{2_2,i}^{(3)}$$

Now we are able to estimate the maximum or minimum error, since the aggregation of the error term is a mixture of multiplications and additions. In Table 2, the maximum error is listed for each comparison matrix as well as the aggregated error for the overall preference vector, where maximal means $\Delta x > 0$. Note that the eigenvectors are normed and small deviations in the results are due to rounding.

Table 2. Ranking of the process areas via error-adjusted AHP

Hierarchy layer	Comparison matrix	$\lambda_{\max}$	Eigenvector to maximum eigenvalue	Error
1	$C_1^{(1)} = \begin{pmatrix} 1 & \frac{1}{4} \\ 4 & 1 \end{pmatrix}$	2	$x_1^{(1)} = \begin{pmatrix} 0.200 \\ 0.800 \end{pmatrix}$	$\Delta x_1^{(1)} = \pm \begin{pmatrix} 0 \\ 0 \end{pmatrix}$
2	$C_2^{(2)} = \begin{pmatrix} 1 & 8 \\ \frac{1}{8} & 1 \end{pmatrix}$	2	$x_2^{(2)} = \begin{pmatrix} 0.889 \\ 0.111 \end{pmatrix}$	$\Delta\, x_2^{(2)} = \pm \begin{pmatrix} 0 \\ 0 \end{pmatrix}$
3	$C_1^{(3)} = \begin{pmatrix} 1 & 3 & 5 & 6 \\ \frac{1}{3} & 1 & 3 & 4 \\ \frac{1}{5} & \frac{1}{3} & 1 & 2 \\ \frac{1}{6} & \frac{1}{4} & \frac{1}{2} & 1 \end{pmatrix}$	4	$x_1^{(3)} = \begin{pmatrix} 0.564 \\ 0.258 \\ 0.110 \\ 0.069 \end{pmatrix}$	$\Delta x_1^{(3)} = \pm \begin{pmatrix} 0.090 \\ 0.008 \\ 0.015 \\ 0.001 \end{pmatrix}$
3	$C_{2_1}^{(3)} = \begin{pmatrix} 1 & 3 & 3 & 4 \\ \frac{1}{3} & 1 & 1 & 2 \\ \frac{1}{3} & 1 & 1 & 2 \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{2} & 1 \end{pmatrix}$	4	$\mathrm{x}_{2_1}^{(3)} = \begin{pmatrix} 0.516 \\ 0.189 \\ 0.189 \\ 0.189 \end{pmatrix}$	$\Delta x_{2_1}^{(3)} = \pm \begin{pmatrix} 0.056 \\ 0.012 \\ 0.012 \\ 0.000 \end{pmatrix}$
3	$C_{2_2}^{(3)} = \begin{pmatrix} 1 & 1 & 4 & 2 \\ 1 & 1 & 4 & 2 \\ \frac{1}{4} & \frac{1}{4} & 1 & 4 \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{4} & 1 \end{pmatrix}$	4	$x_{2_2}^{(3)} = \begin{pmatrix} 0.355 \\ 0.355 \\ 0.076 \\ 0.215 \end{pmatrix}$	$\Delta x_{2_2}^{(3)} = \pm \begin{pmatrix} 0.039 \\ 0.039 \\ 0.013 \\ 0.002 \end{pmatrix}$
Result: $\tilde{r} \pm \Delta\tilde{r} = \begin{pmatrix} 0.511 \\ 0.218 \\ 0.163 \\ 0.108 \end{pmatrix} \pm \begin{pmatrix} 0.061 \\ 0.013 \\ 0.013 \\ 0.001 \end{pmatrix}$				

To check whether rank reversal are likely to appear, Eq. (6) must hold for all entries of the overall preference vector. In our example, this condition is already violated by some of the eigenvalues x at which we checked the entries in the comparison matrices with regard to plausibility. As these entries are plausible, the comparison matrices are not adjusted. However, the condition in Eq. (6) holds for all entries of the overall preference vector in our example. Thus, the decision maker is not indifferent at any entry of the preference vector. Consequently, no additional refinement is needed and the preference vector corresponds to the error-adjusted preference vector, that is, $\tilde{r} = r$. We refer to this phenomenon in section 4.4 in more detail.

4.2 Interactions among Process Areas

To apply the second part of our methodological extension, that is, to determine the relative importance of the interactions between process areas, all interactions s_{ij} among the process areas must be determined. Before we can apply the proposed PageRank-based algorithm, parameter d has to be defined. As stated in section 3.3, when ranking web pages, the original application context of PageRank, d, typically is set to 0.85 (Langville & Meyer, 2011). In the application example, we also set $d = 0.85$. In the first step, the process area network has to be determined. Because Röglinger and Kamprath (2012) assume that all interactions among process areas are symmetric, we have no additional information on the structure of process area networks. Consequently, we define the network ourselves. The network consists of process areas p_1–p_4. The consequential network is described through the adjacency matrix, $W \in \mathbb{R}^{n \times n}$, where element $w_{ji} \in [0,1]$ represents the weight of the link that points from process areas p_j to p_i. All weights and relationships are determined through expert estimates. The weights are included in matrix W, as shown in Table 3.

Table 3. Determining the interactions among process areas via PageRank

Process area network	Process area	Weighted PageRank	Interactions s_{ij}, $i \neq j$
$W = \begin{pmatrix} 0 & \frac{2}{8} & \frac{6}{8} & 0 \\ \frac{2}{6} & 0 & \frac{1}{6} & \frac{3}{6} \\ \frac{1}{6} & \frac{3}{6} & 0 & \frac{2}{6} \\ \frac{1}{8} & \frac{5}{8} & \frac{2}{8} & 0 \end{pmatrix}$	IRP(p_1)	0.188	$s_{12} = 0.099$, $s_{13} = 0.045$, $s_{14} = 0.035$
	SD (p_2)	0.315	$s_{21} = 0.049, s_{23} = 0.117, s_{24} = 0.139$
	OPP (p_3)	0.254	$s_{31} = 0.129, s_{32} = 0.054, s_{34} = 0.061$
	RM (p_4)	0.243	$s_{41} = 0.009, s_{42} = 0.143, s_{43} = 0.081$

Based on process area network W, we can determine the weighted PageRank of each process area p_i using Eq. (8). The resulting weighted PageRank for all four process areas, as shown in Table 3, enables us to determine all directed interactions s_{ij} among the process areas according to Eq. (9). Consequently, applying the method proposed in section 3.3, the relative importance of the relationships among process areas, that is, values s_{ij}, are quantified.

4.3 Result – Scaled Synergy Matrix

In the third and final step, the results of the error-adjusted AHP and PageRank algorithm are scaled and integrated in synergy matrix $S = (s_{ij})_{i,j \in \{1,\ldots,n\}}$. As stated in section 3.4, the scaling should be adapted to enable the comparison of all entries in the synergy matrix. With the scaling proposed in Eq. (10), all results are in the same order of magnitude and independent of n. Thus, all entries in the synergy matrix $S = (s_{ij})$ are comparable. As stated in section 3.4, the results for the interactions between the process areas are already in the right scaling. The entries on the diagonal of the matrix S, that is, the relative importance of the process areas, are transformed according to Eq. (10). Thus, the company sets $s_{11} := \frac{r_1}{n} = \frac{0.511}{4}$, $s_{22} := \frac{r_2}{4}$, $s_{33} := \frac{r_3}{4}$, and $s_{44} := \frac{r_4}{4}$. The overall result of the methodological extension is shown in Eq. (13).

$$S = \begin{pmatrix} 0.128 & 0.099 & 0.045 & 0.035 \\ 0.049 & 0.055 & 0.117 & 0.139 \\ 0.129 & 0.054 & 0.041 & 0.061 \\ 0.009 & 0.143 & 0.081 & 0.027 \end{pmatrix} \tag{13}$$

The synergy matrix can be used in objective functions of decision calculi related to maturity models, as changes of capability levels of distinct process areas and their effects on the overall maturity level can be determined (e.g. using Eq. (1)). Röglinger and Kamprath (2012) evaluate project candidates that decrease or increase capability levels of process areas with an objective function that values changes in the capability levels and maturity level based on the effects of these candidates on the company's firm value. With this procedure, the authors identify projects that should be implemented in order to maximize the added value to the company.

4.4 Interpretation of Results and Discussion

When analysing the results of the demonstration example, the synergy matrix presented in section 4.3 is of main interest, as this matrix is the overall result of the proposed methodological extension. The diagonal of the matrix represents the importance of each process area. These weightings are determined with an error-adjusted AHP approach. According to these results, the company identifies IRP (p_1) as the most important process area for its goal, that is, to extend service customization. SD (p_2) is the second most important process area, followed by OPP (p_3). RM (p_4) is the least important process area. Although p_2, p_3, and p_4 are less important than p_1, they are considered with a weight bigger than zero. An interesting phenomenon can be observed in more detail when analysing the results of the error-adjusted AHP approach, that is, the preference vector. As analysed in section 4.1, the preference vector shows a unique ranking, as the error intervals do not overlap. Consequently, the preference vector is robust and rank reversals are unlikely. However, when analysing the intermediate results, that is, the local matrices, it is noticeable that the ranking is not robust, as the decision maker is indifferent at some alternatives and some local error intervals overlap. An example is $x^{(3)}_{2_2,1} = 0.355 = \mathrm{x}^{(3)}_{2_2,2}$. In other words, even if the ranking on the third level of the AHP hierarchy is not unique and robust, the overall preference vector is robust. Compared with the results of the original example of Röglinger and Kamprath (2012), some differences can be observed, although the absolute height of the entries in the matrices are not directly comparable due to differences in the scaling between both examples. In the original example, all process areas are assumed equally important. In addition, all interactions among process areas are assumed symmetric. The synergy matrix is not scaled, whereas the results in the matrix are not comparable. By contrast, we demonstrate that the importance of all process areas within the demonstration example can differ substantially. For instance, process area p_1 is more than twice as important as process area p_2. In addition, we show that the interactions among process areas are not necessarily symmetric, that is, the interactions among two process areas are not identical. An example is $s_{12} = 0.099$ and $s_{21} = 0.049$. This means that process area p_1 has a greater influence on process area p_2 than vice versa.

The example intended to illustrate the application of the methodological extension for a distinct usage context. A further analysis or interpretation of the results is not reasonable, as for this specific purpose, the example is based on a fictitious company and data. When applying the methodological extension to a decision framework, additional data are needed. Some overall information is given by the management or the company at hand. For instance, the company goals are mostly defined by the management or internal stakeholders. Other data can be gathered by decision makers. For instance, to apply the proposed AHP method, decision makers must create comparison matrices. Thus, the results of this method depend on the analytical skills of the decision makers involved. The decision makers should be very familiar with the company's strategy, performance measurement, and the structure and dependencies in the company. To support the decision makers, they can use information contained in the maturity model, as some maturity models contain very detailed descriptions of capability areas and information about potential dependencies among capability areas that support data collection. The example stimulates further research that is discussed more in detail in the conclusion.

5 Conclusion

In this study, we investigated how maturity models can be enhanced for a prescriptive purpose of use, considering the importance of capability areas and the impact of all interactions among capability areas. To answer this research question, we proposed a methodological extension that can be applied to several maturity models. Because the CMMI blueprint is a quasi-standard for maturity models, we used the decision framework of Forstner et al. (2014) as a reference point for implementing our methodological extension. In addition, it is reasonable to build on this decision framework, as it already extends maturity models for prescriptive purposes. With our extension, maturity models can be enhanced such that they account for the importance of multiple capability areas and consider the impact of the interactions among capability areas even if multiple competing company goals exist. In the first step, we applied an error-adjusted AHP approach (Tomashevskii, 2015) to determine the relative importance of distinct capability areas with regard to multiple company goals. With the applied enhancement to the AHP, the main criticism of the AHP can be overcome. In the second step, we adjusted parts of the Google PageRank (Langville & Meyer, 2011) to receive weights for the interactions among capability areas. Based on both components, a synergy matrix was created for use in the objective functions of decision calculi related to maturity models. In addition, we reported on the results of an application example based on Röglinger and Kamprath (2012). The example intended to demonstrate the application of the methodological extension for a distinct usage context.

Our methodological extension has three main contributions. First, we enhanced maturity models for a prescriptive purpose of use. In addition, we resolved simplifying assumptions of prevailing maturity models and decision frameworks, based on maturity models, for example, the former assumption of symmetric interactions that oversimplifies reality. Second, to the best of our knowledge, this is the first application of the error estimation to the whole AHP method (Tomashevskii, 2015), as we used the standard Gaussian error approximation to determine the error-adjusted overall priority vector for distinct capability areas. Third, to answer our research question, we combined methods from both multi-criteria decision-making, that is, the error-adjusted AHP, and network analytics, that is, the Google PageRank.

However, our methodological extension suffers from limitations that stimulate further research. For instance, to apply the proposed AHP method, decision makers must create comparison matrices. Thus, the results of this method depend on the analytical skills of the decision makers involved. As mentioned in section 3.2, the main criticism of the AHP was resolved by applying an error term, but there is further criticism of both the AHP and the PageRank. For instance, as the dampening factor (d) in the PageRank algorithm of course influences the results of our extension, it should be analysed further in future research. These limitations must be kept in mind when applying the methodological extension. Another limitation is that we demonstrated usage of the methodological extension with only one application example, in which one company goal was relevant for decision-making. With more competing company goals, the application becomes more complex. Additional effort for a comprehensive evaluation of the methodological extension to various application contexts should be part of further research, which would improve the approach. Finally, although the methodological extension of this study addresses some criticism of maturity models, additional criticism prevails, and further research should aim to address these issues and further improve maturity models for prescriptive usage.

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