A Project Portfolio Management Approach to Tackling the Exploration/Exploitation Trade-off

Abstract: Organizational ambidexterity (OA) is an essential capability for surviving in dynamic business environments that advocates the simultaneous engagement in exploration and exploitation. Over the last decades, knowledge on OA has substantially matured, covering insights into antecedents, outcomes, and moderators of OA. However, there is little prescriptive knowledge that offers guidance on how to put OA into practice and to tackle the trade-off between exploration and exploitation. To address this gap, we adopted the design science research paradigm and proposed an economic decision model as artefact. The decision model assists organizations in selecting and scheduling exploration and exploitation projects to become ambidextrous in an economically reasonable manner. As for justificatory knowledge, the decision model draws from prescriptive knowledge on project portfolio management and value-based management, and from descriptive knowledge related to OA to structure the field of action. To evaluate the decision model, we discussed its design specification against theory-backed design objectives and with industry experts. We also instantiated the decision model as a software prototype and applied the prototype to a case based on real-world data.

Keywords: Organizational ambidexterity, Exploration, Exploitation, Project portfolio management, Value-based management, Decision model

1 Introduction

In dynamic business environments, organizations face substantial challenges (Agostini et al. 2016; Jansen et al. 2009). On the one hand, they must explore opportunities of innovative products and processes and engage in emerging markets. On the other hand, they must exploit existing products and processes in mature markets via efficient operations (Eisenhardt et al. 2010; Moreno-Luzon et al. 2014; Turner et al. 2013). As exploration and exploitation strive for different objectives and compete for scarce resources, there is a trade-off between both modes (O'Reilly and Tushman 2013). Currently, many organizations fail in developing organizational ambidexterity (OA), the dual capability that enables organizations to tackle the trade-off between exploration and exploitation (exploration/exploitation trade-off) to achieve long-term success in dynamic business environments (Birkinshaw and Gupta 2013; He and Wong 2004). One reason is that organizations do not know how to put OA into practice (He and Wong 2004; Jansen et al. 2006), a circumstance calling for further research (Moreno-Luzon et al. 2014; Pellegrinelli et al. 2015).

Exploration and exploitation are key concepts of OA (Duncan 1976; March 1991; O'Reilly and Tushman 2013). Many disciplines including innovation and technology management, strategic management, or organizational design extensively discussed OA in general as well as exploration and exploitation in particular (Raisch and Birkinshaw 2008; Simsek 2009). Correspondingly, extant OA research can be split into three streams: outcomes, antecedents, and moderators (O'Reilly and Tushman 2013). The first stream supports that OA entails superior firm performance in terms of sales growth, profitability, and operational performance (Gibson and Birkinshaw 2004; He and Wong 2004; Lubatkin et al. 2006). The second stream investigates antecedents of OA, i.e. structures or mechanisms that describe how organizations should balance exploration and exploitation (O'Reilly and Tushman 2013). While early studies favored a temporal sequencing of exploration and exploitation, recent studies make the case for focusing on both modes simultaneously (Siggelkow and Levinthal 2003; Tushman and O'Reilly 1996; Tushman and Romanelli 1985). Simultaneous approaches, in turn, split into structural, contextual, and leadership-based OA, distinguishing whether exploration and exploitation are implemented via dual structures, capabilities of individuals, or leadership processes (Gibson and Birkinshaw 2004; Smith and Tushman 2005; Tushman and O'Reilly 1996). Thereby, structural approaches not only focus on the organizational level, but also on the group and individual level (Heckmann et al. 2016; Lee et al. 2015; Turner et al. 2015). Particularly, structural OA advocates that the exploration/exploitation trade-off can be tackled via projects (Chandrasekaran et al. 2012; Pellegrinelli et al. 2015). However, related work is rare and remains conceptual. The third research stream investigates how environmental factors affect or moderate the relationship among antecedents and firm performance (Auh and Menguc 2005; Jansen et al. 2009; Sidhu et al. 2004).

Our analysis revealed that research on OA is dominated by conceptual and empirical studies. The importance of pursuing exploration and exploitation has been highlighted repeatedly, and the conceptual distinction between both OA modes has been studied intensively (Gibson and Birkinshaw 2004; He and Wong 2004; Jansen et al. 2006). However, there is a lack of prescriptive knowledge that helps organizations to put OA into practice by tackling the exploration/exploitation trade-off. Specifically, there is little knowledge on how organization can prioritize investments in exploration and exploitation over time (O'Reilly and Tushman 2013; Pellegrinelli et al. 2015; Röder et al. 2014). To address this gap and to extend existing conceptual work on OA, we build on the structural approach and leverage knowledge from project portfolio management (PPM) and value-based management (VBM). Correspondingly, our research question is as follows: *How can organizations decide which exploration and exploitation projects they should implement to become ambidextrous in an economically reasonable manner?*

To answer this research question, we adopted the design science research (DSR) paradigm (Gregor and Hevner 2013). Our artefact is an economic decision model that assists organizations in the selection and scheduling of exploration and exploitation projects. The decision model prioritizes project portfolios, i.e. unique compilations of exploration and exploitation projects, in terms of their contribution to the organization's long-term firm value, recommending the implementation of the value-maximizing portfolio. As already outlined, the decision model draws from prescriptive knowledge on PPM, i.e. project portfolio selection and scheduling, and VBM, i.e. objective functions for corporate decision-making as justificatory knowledge. It also leverages descriptive knowledge on OA to structure the field of action.

This setup is sensible for multiple reasons: First, decision models are valid design artefacts (March and Smith 1995). Second, PPM enables the selection and scheduling of projects, while balancing multiple objectives, accounting for constraints, and building on project types with specific effects (Pellegrinelli et al. 2015; Petit 2012). Exploration and exploitation projects, which are used in the proposed decision model, cover both OA modes and their effects. PPM provides sufficient flexibility to cope with dynamic business environments, as once-compiled project portfolios can be reviewed repeatedly (Martinsuo et al. 2014; Petit and Hobbs 2010). PPM is a mature discipline and has been adopted in many companies (Project Management Institute 2013). It has also been shown to be a useful analytical lens for balancing exploration and exploitation (Pellegrinelli et al. 2015). Third, value orientation is an accepted paradigm of corporate decision-making that enables decisions in line with the objective of maximizing an organization's long-term firm value (Buhl et al. 2011; Damodaran 2012; vom Brocke and Sonnenberg 2015). VBM complements PPM, as it provides objective functions for the comparison of decision alternatives, i.e. project portfolios, by integrating project effects into a single economic value judgment (Bolsinger 2015). Only the combined application of PPM and VBM in the OA context enables determining which exploration and exploitation projects organizations should implement to become ambidextrous in an economically reasonable manner. Finally, this study builds on and extends our prior work on business process improvement and capability development by focusing on the exploration/exploitation trade-off and taking a PPM perspective (*anonymized*).

Our study is structured along the DSR process provided by Peffers et al. (2008). Having identified and justified the research problem in this section, we compile relevant justificatory knowledge and derive design objectives in section 2. In section 3, we outline our research method and evaluation strategy. In section 4, we introduce our decision model's design specification. In section 5, we report on our evaluation activities. We conclude in section 6 by summarizing key results, discussing implications and limitations, and pointing to directions for future research.

2 Theoretical Background

2.1 Organizational Ambidexterity

In general, ambidexterity refers to the ability "to use the right and left hands equally well" (Turner et al. 2015). In particular, OA refers to an organization's dual capability of adapting and responding to environmental change by engaging in exploration and exploitation (Tushmann and O'Reilly 1996). As such, OA is vital for surviving in dynamic business environments (Agostini et al. 2016; Jansen et al. 2009). Below, we provide details on exploration and exploitation, i.e. two key concepts of OA, before we discuss OA from the so-called behavioral and outcome perspectives (Correia-Lima et al. 2013; Simsek 2009). The outcome perspective reflects the first research stream presented in the introduction, whereas the behavioral perspective covers the second stream (O'Reilly and Tushman 2013; Simsek 2009).

Exploration strives for leveraging the opportunities of innovative products and processes (O'Reilly and Tushman 2013). Taking an outside-in perspective, activities associated with exploration are discovery, experimentation, risk-taking, and radical innovation (He and Wong 2004; March 1991). Exploitation strives for the efficient operations of existing products and processes (Pellegrinelli et al. 2015; O'Reilly and Tushman 2008). Taking an inward-driven perspective, associated activities are problem solving, risk reduction, incremental innovation, and continuous improvement (He and Wong 2004; March 1991). As exploration and exploitation strive for different objectives, there is a trade-off between both modes (Turner et al. 2013). In case of extreme exploration, organizations will abound in innovative products and processes, but their economic potential will not be tapped, as learning curve effects are not realized (Prange and Schlegelmilch 2015; Sarkees and Hulland 2009). The operations of existing products and processes is not efficient either. In case of extreme exploitation, organizations feature highly efficient operations, but neglect innovation (Prange and Schlegelmilch 2015; Sarkees and Hulland 2009). They get stuck in evolution and run out of growth prospects (Levinthal and March 1993; Schilling 2015). Organizations that neglect exploration may be excluded from opportunity spaces (Benner and Tushman 2003). As such extreme strategies jeopardize corporate success, exploration and exploitation must be balanced (O'Reilly and Tushman 2008; Prange and Schlegelmilch 2015; Sarkees and Hulland 2009).

From a behavioral perspective, exploration and exploitation are linked to the resource-based view of the firm and dynamic capability theory, where capabilities are defined as repeatable patterns of action in the use of assets (O'Reilly and Tushman 2008; Wade and Hulland 2004). As stable resource configurations do not guarantee sustained competitive advantage in dynamic business environments, organizations also require capabilities that facilitate and govern change (Collis, 1994; Teece, Pisano, & Shuen, 1997). Thus, capabilities are split into operational and dynamic capabilities (Pavlou and El Sawy 2011). Operational and dynamic capabilities relate to exploitation and exploration, respectively. Operational capabilities refer to the effectiveness and efficiency of daily operations and the organization of work (Winter 2003;

Zollo and Winter 2002). The organization of work can, for example, be characterized via automation degree, number of process/product variants, nonroutine ratio (i.e. the fraction of process executions that require special treatment), or mandatory task ratio (i.e. the fraction of routine tasks that must be executed in nonroutine operations) (Afflerbach et al. 2016; Lillrank 2003; Linhart et al. 2015). Dynamic capabilities, in contrast, integrate, build, and reconfigure operational capabilities (Teece and Pisano 1994; Zollo and Winter 2002). Dynamic capabilities affect an organization's output indirectly through operational capabilities (Helfat and Peteraf, 2003). Dynamic capabilities are split into sensing, seizing, and transforming capabilities (O'Reilly and Tushman 2008; Teece 2007). Sensing comprises the scanning and searching for new technological developments, changing customer needs, or new target markets, or problems (Teece 2007). Seizing capabilities address emerging opportunities and problem solutions by investment strategies and resource allocation (Teece 2007). Transforming refers to the implementation of opportunities and solutions (Teece 2007). Thereby, transforming capabilities reflect an organization's ability to cope with nonroutine activities on short notice (flexibility-to-use) and to implement future exploration and exploitation projects (flexibility-to-change) (Afflerbach et al. 2014; Gebauer and Schober 2005).

From an outcome perspective, exploration and exploitation have different effects (He and Wong 2004; Jansen et al. 2009). As exploration strives for innovative products and processes based on radical innovation, it affects an organization's innovation degree (He and Wong 2004). As, in the beginning, organizations are inexperienced in the operation of innovative products and processes, exploration partly destroys once-achieved learning effects (Sarkees and Hulland 2009). As exploitation strives for efficient operations via continuous improvement and incremental innovation, it primarily affects operational performance (Dumas et al. 2013; O'Reilly and Tushman 2008). Operational performance is a multi-dimensional construct, operationalized in terms of performance criteria such as time, cost, or quality (Franco-Santos et al. 2012; Reijers and Mansar 2005). As improving operational performance regarding one criterion generally worsens other performance criteria, not only a trade-off between exploration and exploitation, but also among performance criteria needs to be resolved (Reijers and Mansar 2005). This leads to the following design objective (DO):

(DO.1) Behavioral and outcome perspective on OA: To address the exploration/exploitation trade-off, it is necessary to develop operational and dynamic capabilities (*behavioral perspective*). It is also necessary to treat operational performance as a multi-dimensional concept and to incorporate performance criteria for exploration and exploitation (*outcome perspective*).

2.2 Project Portfolio Selection and Scheduling

Project portfolios include projects selected to achieve distinct objectives and to accomplish corporate change (Dye and Pennypacker 1999; Project Management Institute 2013). Typically, not all available project candidates can be implemented simultaneously, as they compete for scarce resources (Archer and Ghasemzadeh 1999; Dye and Pennypacker 1999). Thus, PPM deals with the management of project portfolios to facilitate the effective usage of resources, account for project interactions and constraints, and balance stakeholder interests (Pellegrinelli et al. 2015; Project Management Institute 2013). PPM also is an iterative process as once-compiled project portfolios can be reviewed repeatedly to cope with internal and external changes (Stettina and Hörz 2015; Young and Conboy, 2013). As PPM can also be tailored to specific project types (Lehnert et al. 2016b), it is a suitable reference discipline for tackling the exploration/exploitation trade-off in dynamic business environments.

Two essential activities of PPM are project portfolio selection and project scheduling. These activities cover the selection of the most appropriate projects from a list of candidates and the scheduling of selected projects for distinct planning periods in line with pre-defined performance criteria and constraints (Archer and Ghasemzadeh 1999). Project portfolio selection comprises five stages: pre-screening, individual project analysis, screening, optimal portfolio selection, and portfolio adjustment. Starting with a pre-screening, project candidates are checked for strategic alignment and whether they are mandatory. During individual project analysis and screening, candidates are evaluated individually regarding their impact on the performance criteria such as cost, revenue, or customer satisfaction. Project candidates are rejected in case their anticipated effects do not satisfy pre-defined thresholds. The optimal portfolio selection stage selects those projects that jointly meet the performance criteria best. If projects should be scheduled for distinct periods, this also happens in this stage. Finally, the optimal project portfolio can be adjusted if needed.

To make sensible project selection and scheduling decisions, it is vital to account for project interactions and constraints, for example latest completion dates or limited budgets (Lehnert et al. 2016b). Project interactions can be split into inter-temporal vs. intra-temporal, deterministic vs. stochastic, and scheduling vs. no scheduling interactions (Kundisch and Meier 2011). Individual project portfolios are affected by intra-temporal interactions, whereas decisions on future projects depend on inter-temporal interactions (Gear and Cowie 1980). Inter-temporal project interactions affect in which order projects can be implemented (Bardhan et al. 2004). A common inter-temporal interaction is a predecessor-successor relationship, where one project depends on the outcome of another project (Lehnert et al. 2016b). As for intra-temporal interactions, an example is that two projects require the same scarce resource, e.g. special equipment or a specific expert, such that they must not be scheduled for the same period (Lehnert et al. 2016b). If project effects are certain or were estimated as single values, interactions are deterministic. If project effects are treated as random variables and information about probability distributions are leveraged for decision-making purposes, they are stochastic (Medaglia et al. 2007). Scheduling interactions only occur if projects may start in different planning periods.

Beyond project portfolio selection and scheduling, PPM encompasses the continuous monitoring of project implementation to ensure the realization of benefits (Beer et al. 2013; Rad and Levin 2006). Thus, project portfolio selection and scheduling are not one-off tasks *(*Martinsuo and Lehtonen 2007; Petit 2012). Rather, they should be executed repeatedly to review project portfolios (Kester et al. 2011). Such reviews entail the reassessment of once-estimated project effects as internal and external changes may cause the deletion, cancellation, or reprioritization of projects. It may also be necessary to add projects (Martinsuo et al. 2014; Petit and Hobbs 2010). Thus, we specify the following design objective:

(DO.2) *Project portfolio selection and scheduling*: To tackle the exploration/exploitation trade-off, it is necessary to consider only projects that align with an organization's corporate strategy, evaluate projects individually before compiling them into project portfolios, consider project interactions and constraints, and continuously review once-compiled project portfolios.

3 Research Method and Evaluation Strategy

Our study follows the DSR process by Peffers et al. (2008). Our artefact is an economic decision model that assists organizations in selecting and scheduling exploration and exploitation projects to maximize their firm value. The model refers to the optimal portfolio selection stage of Archer and Ghasemzadeh's (1999) project portfolio selection process. To specify the decision model's design specification in the design and development phase, we combined normative analytical modeling and multi-criteria decision analysis as research methods. Normative analytical modelling captures the essentials of decision problems in terms of mathematical representations to produce prescriptive results (Meredith et al. 1989). Multi-criteria decision analysis helps structure decision problems by incorporating multiple decision criteria, resolving conflicts, and appraising value judgments (Keeney and Raiffa 1993).

Combining normative analytical modeling and multi-criteria decision analysis is sensible for three reasons: First, tackling the exploration/exploitation trade-off from a PPM perspective requires valuating competing alternatives, i.e. project portfolios. Second, the valuation of project portfolios requires measuring the effects of exploration and exploitation projects via performance criteria and resolving trade-offs. Third, the number of project portfolios usually is such high that they cannot be valued manually. Decision models are beneficial as they serve as formal requirements specification for software prototypes, which automate both the compilation and valuation of project portfolios.

Cohon (2013) proposed a six-step procedure for solving multi-criteria problems: (1) identification and mathematical modeling of relevant decision criteria, (2) definition of decision variables and constraints, (3) data collection, (4) generation and valuation of alternatives, (5) selection of the preferred alternative, and (6) implementation of the selected alternative. In addition, assumptions should be made transparent. Steps (1) and (2) are crucial for the development of the decision model, whereas steps (3) to (5) relate to the application of the decision model. To develop the decision model's design specification, we proceeded as proposed by Cohon (2013). First, we introduce the decision model's general setting in section 4.1 and a layered conceptual architecture in section 4.2. In sections 4.3 to 4.5, we derive and formalize decision criteria for each layer based on the literature to capture the effects of exploration and exploitation projects. Finally, we integrate these criteria in an objective function that serves as decision variable.

To demonstrate and evaluate our decision model, we adopted Sonnenberg and vom Brocke's (2012) evaluation framework, which covers two evaluation dimensions: ex-ante/ex-post and artificial/naturalistic evaluation (Pries-Heje et al. 2008; Venable et al. 2012). Ex-ante evaluation is conducted before an artefact is instantiated, while ex-post evaluation happens after instantiation. Naturalistic evaluation requires artefacts to be challenged by real people, tasks, or systems. Artificial evaluation takes places in controlled settings. The evaluation framework comprises four activities: EVAL1 to EVAL4 (Pries-Heje et al. 2008; Venable et al. 2012). EVAL1 refers to the identification and justification of the DSR problem and the derivation of design objectives to assess whether artefacts address the research problem. We reported on these activities in sections 1 and 2. EVAL2 strives for validated design specifications in terms of real-world fidelity and understandability. To validate the decision model's design specification, we discussed it against the design objectives and with industry experts. We report on results in sections 5.1 and 5.2. EVAL3 strives for artificially validated artefact instantiations to provide a proof of concept. To do so, we implemented the decision model as a software prototype, which we sketch in section 5.3. Representing the most elaborate evaluation activity, EVAL4 validates the applicability and usefulness of artefact instantiations in naturalistic settings, covering steps (3) to (5) of Cohon's procedure for solving multi-criteria problems. We applied the software prototype to real data. We reflect on the results of the prototype application in section 5.3. Although this comes close to a full-fledged EVAL4, we applied the prototype to real-world data, not in an entirely naturalistic setting. This is planned for future research.

4 Design Specification of the Decision Model

4.1 General Setting

The decision model helps determine which exploration and exploitation projects an organization should implement in which order become ambidextrous in an economically reasonable manner. Its unit of analysis are project portfolios, i.e. exploration and exploitation projects that have been scheduled for distinct planning periods in line with project interactions and constraints (Lehnert et al. 2016b). Based on the principles of VBM, corporate decision-making strives for maximizing an organization's long-term firm value. Thus, the decision model uses the risk-adjusted expected net present value (NPV), an acknowledged proxy of an organization's long-term firm value, to valuate and compare project portfolios (Buhl et al. 2011; vom Brocke and Sonnenberg 2015). The decision model recommends the implementation of the value-maximizing portfolio. The value-maximizing portfolio represents the economically most reasonable way for the organization to become ambidextrous and to balance exploration and exploitation over time, based on the project candidates at hand. Importantly, the decision model does not aim to estimate the real NPV of project portfolios as precisely as possible, but to compare portfolios based on a consistent calculation logic. With OA being vital in dynamic environments, the decision model needs to be applied repeatedly. This enables accounting for internal and external changes by adjusting, cancelling, or deleting projects, by adding new projects, or by re-assessing project effects.

The decision model covers the optimal portfolio selection stage of Archer and Ghasemzadeh's (1999) reference process. Thus, it requires a list of project candidates as input, which have already been checked for strategic fit. In addition, the effects of these candidates must have been estimated and challenged in the individual project analysis and screening stages. In the optimal portfolio selection stage, the decision model calculates the risk-adjusted expected NPV for all admissible project portfolios, i.e. portfolios that do not violate project interactions or constraints. The number of admissible project portfolios usually is large due to the combinatorial complexity entailed by project selection and scheduling.

To illustrate how the decision model is working, Figure 1 shows four exemplary project portfolios based on exploitation and exploration projects. For example, portfolio 1 includes all projects, where "Explore 1" and "Exploit 2" are scheduled for the first period, "Explore 3" for the second, and "Explore 2" and "Exploit 1" for the third period. In addition, we assume that there are two interactions: "Explore 1" and "Explore 3" require the same domain expert, and "Explore 3" requires the output of "Exploit 2". Thus, "Explore 1" and "Explore 3" must not be scheduled for the same period (intra-temporal interaction), and "Exploit 2" must be finished before "Explore 3" can start (inter-temporal interaction). In the example, portfolios 2 and 3 are not admissible as portfolio 2 violates the intra-temporal interaction, whereas project portfolio 3 violates the inter-temporal interaction. Portfolios 1 and 4 are admissible and valuated in terms their risk-adjusted expected NPV. Here, portfolio 1 is the value-maximizing portfolio.

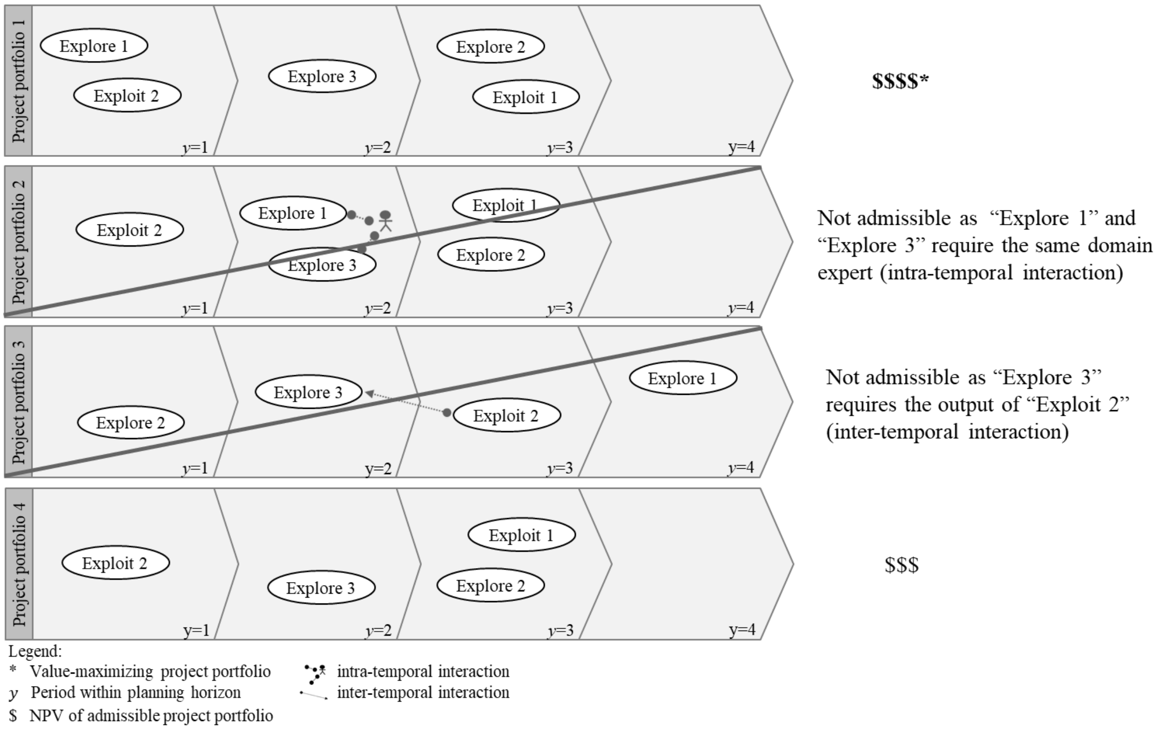

Figure 1. Example of the optimal portfolio selection stage

4.2 Conceptual Architecture

As mentioned in section 4.1, the decision model calculates the risk-adjusted expected NPV of admissible project portfolios by linking the effects of exploration and exploitation projects across multiple planning periods. To do so, the decision model builds on a conceptual architecture with three layers: *project layer*, *behavioral layer*, and *outcome layer*. **Fehler! Verweisquelle konnte nicht gefunden werden.** shows the conceptual architecture for a single period. After a high-level overview in this section, we define each criterion layer-by-layer based on the literature and provide examples in sections 4.3 to 4.5. We also outline assumptions and propose mathematical equations that formalize the relations among the criteria. We critically reflect on assumptions in section 5.1. An overview of all mathematical variables used in the decision model can be found in Appendix 1.

The *project layer* is the basis for the compilation of project portfolios (Lehnert et al. 2016b). It includes exploration and exploitation project to cover both OA modes (Duncan 1976; March 1991). This separation is rooted in the structural approach (Pellegrinelli et al. 2015). In line with the behavioral perspective (O'Reilly and Tushman 2008; Wade and Hulland 2004), the *behavioral layer* uses knowledge on operational capabilities to cover how operations are organized (Zollo and Winter 2002). As for dynamic capabilities, the behavioral layer covers an organization's transforming capabilities (Teece 2007). The decision model abstracts from sensing and seizing capabilities, a decision that we reflect in section 5.1. Drawing from the outcome perspective (He and Wong 2004; Jansen et al. 2009), the *outcome layer* uses knowledge on VBM and performance measurement (Buhl et al. 2011; Franco-Santos et al. 2012; Reijers and Mansar 2005). It includes monetary and non-monetary performance criteria for exploration, e.g. innovation degree, and exploitation, e.g. quality and time (Dumas et al. 2013; He and Wong 2004). In single planning periods, monetary and non-monetary performance criteria are aggregated into the periodic cash flow, an input parameter of the risk-adjusted expected NPV. Defined as the sum of periodic cash flows discounted by a risk-adjusted interest rate, the risk-adjusted expected NPV covers all planning periods and enables comparing project portfolios (Copeland et al. 2005; Damodaran 2012).

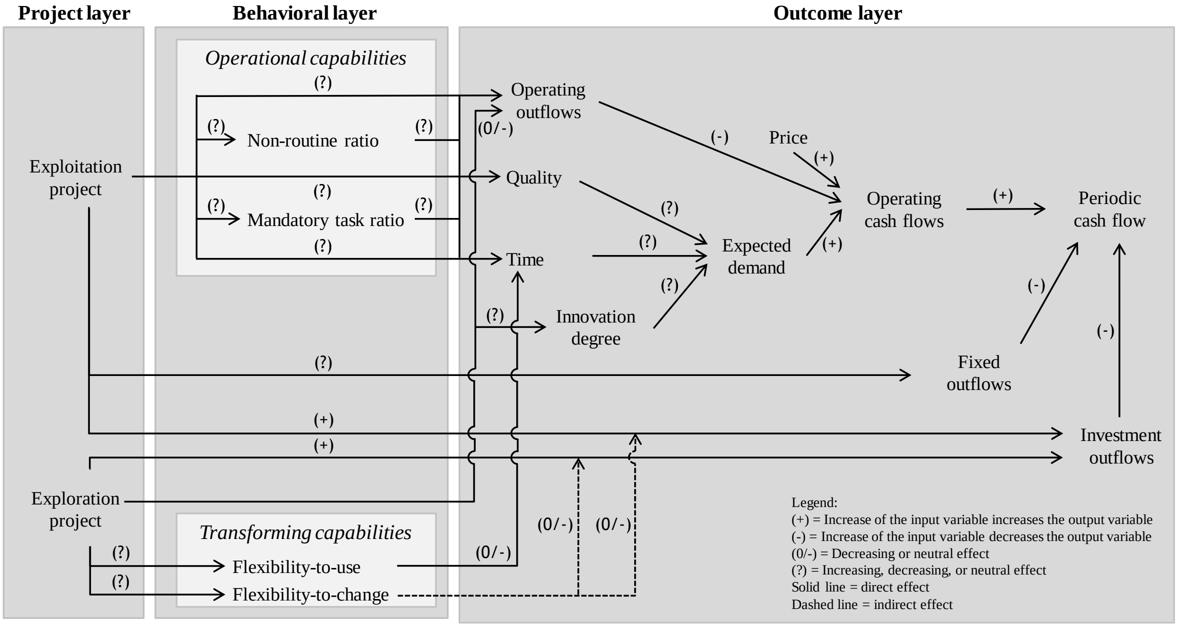

Figure 2. Conceptual architecture of the decision model (single-period view)

As depicted in Figure 2, exploration and exploitation projects influence the criteria included in the behavioral and the outcome layer. Further, the criteria from the behavioral and the outcome layer are linked as operational and non-monetary performance criteria must be monetized to calculate periodic cash flows and the risk-adjusted expected NPV (Bolsinger 2015; Damodaran 2012). To do so, we distinguish between direct and indirect effects. Direct effects either link a project type and a criterion from the behavioral or the outcome layer or two criteria, meaning that one criterion influences the other. For example, this applies to time and demand. Indirect effects moderate direct effects, meaning that a criterion influences the strength of a direct effect. For example, flexibility-to-change moderates the effect of exploration projects on investment outflows. Many effects, particularly those in the outcome layer, have an unambiguous polarity. For example, investment outflows have a negative effect on the periodic cash flow. Other effects, particularly those originating from the project layer, are ambiguous, meaning that they depend on the project at hand (Linhart et al. 2015). For example, while exploitation projects can in general affect time positively, negative, or not at all, the effect of a specific project is unambiguous.

To illustrate how project effects cascade through the conceptual architecture, we provide two examples. First, consider an exploration project that improves an organization’s innovation degree and flexibility-to-use, i.e. its ability to deal with nonroutine activities. The positive effect on flexibility-to-use reduces the processing time. This, in turn, increases the expected demand and results in increased operating and periodic cash flow. Likewise, a higher innovation degree increases the expected demand, and transitively the operating as well as the periodic cash flow. Second, consider an exploitation project that decreases the nonroutine ratio, i.e. the fraction of operations requiring special treatment, and increases processing time. A lower nonroutine ratio decreases the operating outflows and increases quality, a circumstance that increases the demand. However, the exploitation project also increases time, an effect that reduces expected demand. In this example, the positive effect of increased quality and the negative effect of increased time may cancel each other out. Further, both projects cause investment outflows.

4.3 Project Layer

The project layer includes exploration and exploitation projects (Chandrasekaran et al. 2012; O'Reilly and Tushman 2008). This separation helps keep the decision model parsimonious. Hybrid forms, which occur in industry, can be covered by linking exploration and an exploitation projects via project interactions. Below, we overview the effects of both project types, which are also compiled in Appendix along corresponding mathematical variables.

Exploitation Projects

Exploitation projects strive for efficient operations by means of incremental innovation and the development of operational capabilities (O'Reilly and Tushman 2008). On the one hand, exploitation projects can directly influence operational performance criteria, i.e. quality, time, and operating outflows, located in the outcome layer (Dumas et al. 2013; Winter 2003). On the other hand, they can affect those characteristics from the behavioral layer that characterize the organization of work, i.e. nonroutine ratio and mandatory task ratio (Linhart et al. 2015). The latter reflects the fraction of routine tasks also included in nonroutine activities. For example, the implementation of a quality management system may increase quality and fixed outflows. Further, a process standardization project may reduce operating outflows and decrease the nonroutine ratio. All exploitation projects cause investment outflows.

Exploration Projects

Exploration projects strive for radical innovation and the development of an organization's transforming capabilities (O'Reilly and Tushman 2008). On the one hand, exploration projects can improve the organization's innovation degree, while worsening operating outflows. The innovation degree measures an organization's innovativeness as perceived by its customers (He and Wong 2004). The second effect is rooted in the fact that organizations at first have no experience with innovative products and services. Thus, once-achieved cost-reducing experience curve effects are partly destroyed (Sarkees and Hulland 2009). On the other hand, exploration projects can strengthen an organization's flexibility-to-use and flexibility-to-change capabilities, which are known to make nonroutine operations more time-efficient and the implementation of future projects more cost-efficient (Gebauer and Schober 2005; Lehnert et al. 2016b). For example, introducing new product features may improve the innovation degree, while experience curve effects are destroyed, and outflows raise. The implementation of a modular production technology improves flexibility-to-use capabilities. Further, training employees in project management increases an organization's flexibility-to-change capabilities.

As the experts, who participated in the decision model's evaluation, suggested, the decision model accounts for incremental and radical innovation (Schilling 2015). Incremental innovation can be implemented by exploitation projects, i.e. small improvements of routine operations, whereas radical innovation is captured via exploration projects, i.e. next-generation products or extensions of existing products or services. The decision model thus abstracts from disruptive innovation, as related effects are difficult to estimate and cannot be reasonably integrated in a decision model that schedules projects to multiple planning periods in advance (Schilling 2015).

To account for the effects of both project types, we assume (Lehnert et al. 2016b): *Project effects become manifest immediately after project completion. They can be assessed independently from other projects, available as relative numbers and linked multiplicatively*. *Projects can take differently long, and multiple projects can be implemented in parallel to enable simultaneous engagement in exploration and exploitation.* We discuss implications of this assumption in section 5.1.

4.4 Behavioral Layer

Operational Capabilities

The behavioral layer covers criteria related to an organization's operational and transforming capabilities. Operational capabilities refer to the efficiency and effectiveness of daily operations and the organization of work (Winter 2003; Zollo and Winter 2002). Operations are typically streamlined by standardization and automation (Karmarkar 2014; Johnston et al. 2012). Thereby, routine and nonroutine operations must be distinguished as both have a different performance. While routine operations handle processes with well-defined inputs and outputs, nonroutine operations handle activities that require special treatment (Lillrank 2003). Two useful criteria for distinguishing routine and nonroutine operations are nonroutine ratio and mandatory task ratio (Linhart et al. 2015). The nonroutine ratio captures the fraction of activities that require special treatment. The mandatory task ratio indicates which fraction of routine activities are also included in nonroutine operations. Both ratios can be influenced by exploitation projects. Their value in a distinct period depends on their initial value and related effects of previously implemented exploitation projects. Eq. 1 and Eq. 2 quantify this relationship.

$$N_y = N_0 \cdot \prod_{j \in \mathrm{EXPLOIT\_COMP}_{y-1}} o_j \qquad \text{(Eq. 1)}$$

$$M_y = M_0 \cdot \prod_{j \in \mathrm{EXPLOIT\_COMP}_{y-1}} p_j \qquad \text{(Eq. 2)}$$

Transforming Capabilities

Transforming capabilities capture an organization's ability to reconfigure operational capabilities and facilitate change (Teece 2007). As flexibility is closely related to organizational change, we use related knowledge to operationalize transforming capabilities (Afflerbach et al. 2014). Gebauer and Schober (2005) distinguish flexibility-to-use and flexibility-to-change. Flexibility-to-use makes nonroutine operations more time-efficient, as it reduces preparation and setup times. For instance, the implementation of a modular production technology improves flexibility-to-use, which reduces the processing time of nonroutine operations. Flexibility-to-change makes the implementation of projects more cost-efficient (Lehnert et al. 2016b). This can be achieved by training employees in project management methods. Flexibility-to-use and -change can be affected by exploration projects. Their value in a distinct period depends on their initial value and related effects of previously implemented exploration projects. The respective formulae are shown in Eq. 3 and Eq. 4.

$$F_y^{\mathrm{use}} = F_0^{\mathrm{use}} \cdot \prod_{j \in \mathrm{EXPLORE\_COMP}_{y-1}} b_j \qquad \text{(Eq. 3)}$$

$$F_y^{\mathrm{change}} = F_0^{\mathrm{change}} \cdot \prod_{j \in \mathrm{EXPLORE\_COMP}_{y-1}} c_j \qquad \text{(Eq. 4)}$$

4.5 Outcome Layer

Risk-adjusted Expected Net Present Value

The outcome layer covers monetary and non-monetary performance criteria. These criteria are directly influenced by exploration and exploitation projects, or transitively via criteria from the behavioral layer. From a single-period perspective, which is taken in Figure 2, performance criteria are successively monetized and aggregated to the periodic cash flow (Bolsinger 2015). From a multi-periodic perspective, periodic cash flows influence the risk-adjusted expected NPV, which is the decision model's objective function and used to compare project portfolios (Damodaran 2012). Below, we first provide details on the risk-adjusted expected NPV, before elaborating on its components.

The risk-adjusted expected NPV, as shown in Eq. 5, measures the value contribution of a project portfolio as the sum of its discounted periodic cash flows based on a risk-adjusted interest rate (Copeland et al. 2005; Damodaran 2012). The *argmax* function used in Eq. 5 returns the value-maximizing portfolio. The risk-adjusted expected NPV builds on the periodic cash flows, which are split into investment outflows, fixed outflows, and operating cash flows (Lehnert et al. 2016b). Investment outflows accrue for the implementation of projects. By definition, fixed outflows occur independently from the demand, i.e. no matter how many products and services are sold. An example is the maintenance of a production system or workflow management system. In contrast, operating cash flows depend on the expected demand, sales price, and operating outflows. The demand reflects how many products and services are sold. In our decision model, the demand is driven by time, quality, and innovation degree (Linhart et al. 2015; Oubiña et al. 2007). As the demand is highly company-specific, we do not further specify it here. The price mirrors how much customers pay per unit of sold products and services, and it is assumed to be constant. Finally, operating outflows accrue for the production of products and services. To complete the presentation of the decision model, we elaborate on each component of the NPV below.

$$\begin{aligned} r^* &= \underset{r \epsilon R}{\operatorname{argmax}} NPV_r \\ &= \underset{r \epsilon R}{\operatorname{argmax}} \sum_{y=0}^{Y} \frac{CF_y^{\text{per}}}{(1+z)^y} \\ &= \underset{r \epsilon R}{\operatorname{argmax}} \sum_{y=0}^{Y} [-\frac{O_y^{\text{inv}}}{(1+z)^y} - \frac{O_y^{\text{fix}}}{(1+z)^y} + \frac{CF_y^{\text{op}}}{(1+z)^{y+1}}] \\ &= \underset{r \epsilon R}{\operatorname{argmax}} \sum_{y=0}^{Y} [-\frac{O_y^{\text{inv}}}{(1+z)^y} - \frac{O_y^{\text{fix}}}{(1+z)^y} + \frac{n(t_y, q_y, i_y) \cdot (p - O_y^{\text{op}})}{(1+z)^{y+1}}] \end{aligned} \quad \text{(Eq. 5)}$$

Investment Outflows

The investment outflows in a distinct period depend on the exploration and exploitation projects that are currently running in that period. As the decision model allows for scheduling several projects for one period as well as differently long projects, the investment outflows can encompass several projects. In addition, they depend on the flexibility-to-change level that has been achieved by the prior implementation of exploration projects. Both effects are shown in (Eq. 6).

$$O_y^{\text{inv}} = \sum_{j \in (\text{EXPLOIT\_RUN}_y \cup \text{EXPLORE\_RUN}_y)} O_j^{\text{inv}} \cdot F_y^{\text{change}} \quad \text{(Eq. 6)}$$

Fixed Outflows

In line with the differentiation between routine and nonroutine operations, there are fixed outflows for routine operations, e.g. for wages or standard IT services, and nonroutine operations, e.g. for preparatory tasks or configurable IT services. The total fixed outflows in a distinct period depend on the initial fixed outflows for routine and nonroutine operations as well as on related effects of previously implemented exploitation projects. The formulae are shown in equations Eq. 7 to Eq. 9.

$$O_y^{\text{fix}} = O_y^{\text{fix,R}} + O_y^{\text{fix,NR}} \tag{Eq. 7}$$

$$O_y^{\text{fix,NR}} = O_0^{\text{fix,NR}} \cdot \prod_{j \in \text{EXPLOIT\_COMP}_{y-1}} m_j \tag{Eq. 8}$$

$$O_y^{\text{fix,R}} = O_0^{\text{fix,R}} \cdot \prod_{j \in \text{EXPLOIT\_COMP}_{y-1}} n_j \tag{Eq. 9}$$

Operating Outflows

The average total operating outflows must account for routine and nonroutine operations, too. To do so, the nonroutine ratio weighs the outflows for routine and nonroutine operations, as shown in Eq. (10). The operating outflows for both routine and nonroutine operations in a distinct period depend on their initial values and related effects of all exploitation projects completed so far. The operating outflows for nonroutine operations further comprise the fraction by which nonroutine operations include routine tasks as represented by the mandatory task ratio as well as outflows that capture additional effort for nonroutine operations, e.g. for extensive manual work. This is shown in Eq. 11. Operating outflows for routine operations are reduced by experience curve effects, as shown in Eq. 12. There are no experience curve effects for nonroutine operations due to their non-repetitive character. Experience curve effects capture the positive effects of executing routine operations (Henderson 1973). The more demand is handled by routine operations, the higher the experience curve effects. This is because operating outflows drop by a constant factor each time the cumulated demand doubles (Henderson 1973). This effect is formalized via a power law function with constant elasticity, as shown in (Eq. 13). However, radical innovation as implemented via exploration projects partly destroys experience curve effects, as the cumulated demand is partly reset (Sarkees and Hulland 2009).

$$O_y^{\text{op}} = O_y^{\text{op,R}} \cdot (1 - N_y) + O_y^{\text{op,NR}} \cdot N_y \tag{Eq. 10}$$

$$O_y^{\text{op,NR}} = M_y \cdot O_y^{\text{op,R}} + \Delta O_0^{\text{op,NR}} \cdot \prod_{j \in \text{EXPLOIT\_COMP}_{y-1}} k_j \tag{Eq. 11}$$

$$O_y^{\text{op,R}} = O_0^{\text{op,R}} \cdot E_y \cdot \prod_{j \in \text{EXPLOIT\_COMP}_{y-1}} l_j \tag{Eq. 12}$$

$$E_y = (d_j \cdot CD_{y-1})^{-\alpha} \tag{Eq. 13}$$

Time

Time and operating outflows can be treated similarly, as both depend on criteria from the behavioral layer. Thus, the average total processing time consists of a component for routine and nonroutine operations, weighted by the nonroutine ratio, as shown in Eq. (14). The processing time of routine operations covers waiting time and working time, whereas for nonroutine operations, additional time must be considered to capture more complex work and setup. Based on the mandatory task ratio, the processing time of nonroutine operations partly depends on the processing time of routine operations. The additional processing time for nonroutine operations also depend on the organization's flexibility-to-use capabilities. The average total processing time in a given period depends on the initial processing time of routine and nonroutine operations and time effects of previously implemented exploitation projects. This is formalized in Eq. (15) and Eq. (16).

$$t_y = t_y^{\mathrm{R}} \cdot (1 - N_y) + t_y^{\mathrm{NR}} \cdot N_y \tag{Eq. 15}$$

$$t_y^{\mathrm{NR}} = M_y \cdot t_y^{\mathrm{R}} + \Delta t_0^{\mathrm{NR}} \cdot F_y^{\mathrm{use}} \cdot \prod_{j \in \mathrm{EXPLOIT\_COMP}_{y-1}} e_j \tag{Eq. 16}$$

$$t_y^{\mathrm{R}} = t_0^{\mathrm{R}} \cdot \prod_{j \in \mathrm{EXPLOIT\_COMP}_{y-1}} f_j \tag{Eq. 17}$$

Quality

The average total quality in a distinct period depends on the nonroutine ratio as well as on the quality of routine and nonroutine operations. This is shown in Eq. (18). As there is no direct relationship between routine and nonroutine quality, both can be assessed independently (Linhart et al. 2015). Moreover, they depend on their initial value and the quality effects of previously implemented exploitation projects, as shown in Eq. (19) and Eq. (20). To account for the property that quality typically has an upper boundary, e.g. error rates cannot exceed 100%, the decision model integrates such a boundary in Eq. (17) (Dumas et al. 2013; Leyer et al. 2015). Thus, money may be wasted if an exploitation project with strong quality effects is implemented and quality is already very close to its upper boundary.

$$q_y = \min(q_y^{\mathrm{total}}; q^{\max}) \tag{Eq. 18}$$

$$q_y^{\mathrm{total}} = q_y^{\mathrm{R}} \cdot (1 - N_y) + q_y^{\mathrm{NR}} \cdot N_y \tag{Eq. 19}$$

$$q_y^{\mathrm{NR}} = q_0^{\mathrm{NR}} \cdot \prod_{j \in \mathrm{EXPLOIT\_COMP}_{y-1}} g_j \tag{Eq. 20}$$

$$q_y^{\mathrm{R}} = q_0^{\mathrm{R}} \cdot \prod_{j \in \mathrm{EXPLOIT\_COMP}_{y-1}} h_j \tag{Eq. 21}$$

Innovation Degree

Finally, the innovation degree measures an organization's innovativeness as perceived by its customers (He and Wong 2004). To calculate the innovation degree, it is not necessary to distinguish between routine and nonroutine operations. Further, the innovation degree is influenced by exploration projects. Accordingly, the innovation degree in a distinct period depends on its initial value, the positive effects of all previously implemented exploration projects, and the negative effects of all degeneration effects accumulated up to that period. This is shown in Eq. (21). The decision model features a degeneration effect to penalize if the organization focuses too much on exploitation. This is common as the innovativeness of products and services perceived by customers decreases over time if the organization does not invest in exploration (Schilling 2015).

$$i_y = i_0 \cdot \prod_{j \in \mathrm{EXPLORE\_COMP}_{y-1}} a_j \tag{Eq. 22}$$

5 Evaluation

5.1 Feature Comparison

In line with our evaluation strategy, we discussed the decision model's design specification against the design objectives and with industry experts. The discussion against the design objectives, an artificial evaluation method known as feature comparison, helps assess whether the decision model addresses the research problem. In contrast, expert interviews helped challenge the decision model's real-world fidelity and understandability. In sum, feature comparison revealed that the decision model addresses both design objectives, but not to the full extent. The decision model is beset with limitations from a theoretical perspective for the sake of increased applicability. However, as supported by the experts' feedback, the decision model is understandable for analytically versed practitioners from medium-sized and larger organizations, and it covers most constellations that occur in industry settings. We discuss the results of feature comparison and the expert interviews below.

Regarding design objective (DO.1), which refers to the behavioral and outcome perspectives, the decision model builds on exploration and exploitation projects to cover both modes. Admittedly, the distinction between exploration and exploitation projects is simplifying. However, the decision model can deal with hybrid forms, which occur in industry, by linking exploitation and exploration projects via project interactions. Both project types have distinct effects on characteristics of operational and transforming capabilities from the behavioral layer as well as on the innovation degree and operational performance criteria from the outcome layer, which are aggregated to the risk-adjusted expected NPV. All project effects included in the decision model are backed by literature. Although the risk-adjusted expected NPV is an accepted objective function, it accounts only implicitly for the risks associated with corporate decisions via a risk-adjusted interest rate. This complies with the decision model's focus on deterministic project effects, an assumption we discuss below. Theoretically, it would be possible to account for risks more explicitly, e.g. via probability distributions and certainty equivalents. However, this would considerably increase the decision model's complexity and reduce its applicability. For example, the incorporation of project effects with probability distributions typically prohibits that the optimal project portfolio can be determined analytically. Instead, simulation or complex numerical approaches are required. As for dynamic capabilities, the decision model focuses on transformation capabilities. This is reasonable as sensing capabilities, i.e. the detection of opportunities, problems, and changes, become manifest between subsequent applications of the decision model. Hence, we recommended applying the decision model repeatedly. As for seizing capabilities, i.e. the determination of investment strategies, the decision model itself contributes to an organization's seizing capabilities, as it guides the selection and scheduling of exploration and exploitation projects.

As for design objective (DO.2), which refers to project portfolio selection and scheduling, the decision model is located at the optimal portfolio selection stage of Archer and Ghasemzadeh's (1999) reference process. Thus, it requires the results of all previous stages as input. The decision model also caters for various project interactions and constraints. However, it assumes that project effects are deterministic, can be assessed prior to the application of the decision model in terms of relative numbers, and become manifest immediately after project completion. Though being common, these assumptions simplify reality. The reason for focusing on deterministic effects is that stochastic effects entail much more data collection effort and can hardly be assessed in naturalistic settings, if at all. While the consideration of stochastic effects would increase real-world fidelity, it would substantially increase the model's complexity reduce applicability. As shown in the prototype application, a scenario approach using optimistic and pessimistic parameter estimations is a viable compromise. Second, the ex-ante assessment of relative project effects simplifies data collection and enables multi-period decision-making. The absolute magnitude of such effects depends on all previously implemented projects and becomes manifest when project portfolios are valuated. Otherwise, project effects had to be estimated for all projects combinations that may be implemented before. This is infeasible owing to interdependencies and estimation inaccuracies (Beer et al. 2013). Thus, we recommended applying the decision model repeatedly to continuously reassess once-estimated effects. Third, the assumption that effects become manifest immediately after completion neglects that benefits tend to realize with delay and only partially. Our rationale for this assumption is the same as for deterministic effects. Although this assumption leads to an overestimation of NPVs, it does not bias the results, because the calculation logic of the decision model is consistently applied to all project portfolios. Thus, the ranking of the portfolios remains unchanged.

5.2 Expert Interviews

To complement feature comparison, we interviewed industry experts involved in OA-related decision-making. When recruiting experts, we specified the following criteria: Individuals needed more than 10 years' experience, hold a leading position, and have substantial project experience. On the aggregated level, we aimed to cover various departments and industries, as OA is an interdisciplinary phenomenon. We also required the experts to differ by personal and academic backgrounds. We followed a convenience sampling approach, i.e. we invited experts from our personal network (Glaser and Strauss 1967). Aware of the fact that convenience sampling is a nonprobability method, we choose it to gain initial insights into the understandability and real-world fidelity of our decision model (Saunders et al. 2012). Although we could draw from a reliable network, it was hard to compile a sample meeting the criteria above. We conducted interviews with experts until we received no new insights and we agreed that saturation had been reached. In total, we interviewed eight experts as shown in Appendix 2.

We conducted a semi-structured interview with each expert (Myers and Newman 2007). Interviews took about 90 minutes and were attended by two researchers. We provided the experts with an initial version of the decision model's design specification, asking for comments on real-world fidelity and understandability. Having introduced the ideas of exploration, exploitation, and the associated trade-off, we discussed the decision model's conceptual architecture, each criterion, and the effects among them. Overall, the experts supported the relevance of our research and confirmed the research gap. They stated that their organizations are facing the exploration/exploitation trade-off, and that guidance on how to prioritize investments in exploration and exploitation is in high need. Nevertheless, challenges regarding the application of the decision model, the estimation of various input parameters, and the implementation of real-world settings in a simplified way are addressed by the experts. All in all, they considered the decision model a valuable tool. An overview of the experts' feedback and how it was incorporated is included in Appendix 3. Below, we present comprehensive results.

As for real-world fidelity, the experts confirmed that the decision model covers many constellations that occur in their organizations. They appreciated that the decision model builds on the principles of PPM and VBM, while distinguishing between exploration and exploitation projects. In their opinion, PPM provides sufficient flexibility to deal with manifold real-world constellations, whereas VBM enables justifying OA decisions from a business value perspective, an important feature when talking to senior managers. The experts were also fine with the distinction between exploration and exploitation projects as both can be combined. While the experts indicated that it may be difficult to estimate the high number of effects for many projects, they agreed that this problem is not specific for the decision model at hand, but applies to PPM at large. Beyond confirming the effects on monetary and non-monetary performance criteria, the experts stated that important effects included in the decision model also occur in practice: degeneration of the innovation degree, exploration projects' destroying effect on the experience curve, dependency of the demand on quality, time, and innovation degree as well as the moderating effect of transforming capabilities. The experts anticipated that some parameters, i.e. innovation degree, demand, and transforming capabilities, will be hard to estimate, while this is comparatively easily for parameters such as time, quality, and operational outflows. To challenge this assessment, we applied the software prototype to real-world data. Details of the prototype application including potential data sources can be found in Appendix 4. A summary is presented in section 5.3.

Regarding understandability, the experts confirmed that the decision model is understandable for analytically versed experts typically involved in corporate decision-making. According to the experts, the decision model's understandability is supported by its layered architecture, the clear definition of included criteria, and the mathematical formulas that capture the relation among the criteria. The experts indicated that the decision model is highly complex due to many intertwined criteria and its multi-project multi-period nature. Nevertheless, they acknowledged that the exploration/exploitation trade-off is complex itself. A simple decision model would not suffice. Given the model's complexity, the experts also stated that organizations, which plan to use the decision model, require mature PPM and performance measurement capabilities. Thus, the decision model particularly fits project- and data-driven organizations that not only feature mature capabilities, but also dispose of sufficient capacity to apply the decision model and collect data. Admittedly, all interviewed experts have been working with medium-sized or large organizations. Understandability and real-world fidelity of our decision model for small organizations and other industries still needs to be assessed.

Based on the results of feature comparison and the expert feedback, we conclude that the decision model addresses both design objectives. It proposes compromises between the full extent of theoretically possible formalization and applicability. Further, the decision model is understandable for analytically versed experts and covers real-world constellations that typically occur in medium-sized and large organizations. Both evaluation activities showed that the decision model can be further developed in the future. We get back to these indications in section 6.

5.3 Prototype Construction and Application

To provide a proof of concept, we instantiated the decision model's design specification as presented in section 4 as a software prototype. The prototype is necessary to apply the decision model, as the problem complexity heavily grows with the number of projects and periods (Lehnert et al. 2016a). Having provided all input parameters, users can define scenarios by enabling or disabling projects or constraints. The prototype then generates all admissible project portfolios and calculates their value contribution as specified in the objective function. The prototype uses optimistic and pessimistic effects to cater for estimation inaccuracies. Finally, the prototype orders project portfolios by their value contribution.

We also applied the prototype to real-world data to challenge whether the model leads to sensible results, to gain experience in data collection and insights into the decision model's applicability and usefulness. In this section, we only present a summary. Details including all input parameters, potential data sources, and optimization results can be found in Appendix 4. To apply the prototype, we collected data from an industry expert who was working with an organization from the telecommunications industry and who had already participated in the interviews. The expert provided us with input data for the organization's operations, projects, and the general setting. We also defined scenarios. For each scenario, we assessed the optimal and worst project portfolio, while accounting for optimistic and pessimistic project effects.

The prototype construction confirmed that the decision model can be implemented. Currently, the prototype is not a full-fledged software product, but has been developed for research purposes. It focuses on effectivity, i.e. the implementation of the decision model's design specification. Efficiency in terms of fast solution times and a convenient user interface have not been in the center of interest. The application of the prototype illustrated that the decision model returns interpretable portfolios of exploration and exploitation projects for multiple scenarios. We demonstrated that the decision model can be applied and input data can be collected, although the high number of parameters entails substantial data collection effort. As found in the expert interviews, some parameters are hard to estimate. Thus, the decision model should be applied repeatedly, not only to account for changes, but also to gain experience in data collection. As for usefulness, the industry expert was happy with the results as he could interpret the choice of the optimal project portfolio and think about scenarios in a structured manner. Further, the prototype returned concrete solutions for his problem. The expert also confirmed that the decision model as well as a more efficient and user-friendly prototype would support him in work. Thus, we conclude that the decision model is applicable in real-world settings and useful for corporate decision-makers. Nevertheless, we admit that we only gained experience from one case. To further challenge the applicability and usefulness, we recommend conducting additional case studies.

6 Discussion and Conclusion

Given the increasing importance of OA and the lack of related prescriptive knowledge, we investigated how organizations can decide which exploration and exploitation projects they should implement to become ambidextrous in an economically reasonably manner. Adopting the DSR paradigm, our artefact is n decision model that assists organizations in selecting exploration and exploitation projects as well as in scheduling these projects for distinct planning periods. Drawing from prescriptive knowledge on PPM and VBM, the decision model valuates project portfolios based on their contribution to the long-term firm value. The decision model further builds on exploration and exploitation projects to cover both modes of OA. Exploration projects improve an organization's innovation degree, decrease operational performance by partly destroying experience curve effects, and enhance transforming capabilities. Exploitation projects affect operational capabilities, i.e. nonroutine and mandatory task ratio, and operational performance criteria such as time, cost, and quality. We evaluated the decision model by following all activities from Sonnenberg and vom Brocke's (2012) evaluation framework. We validated the decision model's real-world fidelity and understandability by discussing its design specification against theory-backed design objectives and with industry experts. We also instantiated the decision model as a prototype and we applied the prototype to real-world data to gain insights into applicability and usefulness. Below, we first report on limitations, and then point to theoretical and managerial implications.

Our research is beset with limitations related to the decision model's design specification and its evaluation. As we discussed some limitations in section 5, we only sketch them here. As all mathematical models, our decision model includes simplifying assumptions: It only caters for deterministic project effects and treats risks rather implicitly via a risk-adjusted interest rate. The decision model also assumes that project effects become manifest immediately after project completion and that they can be estimated ex-ante in terms of relative numbers independently from other projects. Moreover, in case a project lasts multiple periods, the investment outflows are split proportionately. Most of these assumptions are common in the literature. Nevertheless, they can be relaxed from a theoretical perspective. On the one hand, this would increase the decision model's real-world fidelity. On the other, its applicability would suffer, as data collection causes disproportionate effort. The model would also benefit from further evaluation. We were able to discuss the design specification with eight experts whom we recruited from our personal network. Although we do not consider convenience sampling a limitation itself, we admit that, given its complexity, the decision model should be discussed with further experts. The same holds for the application of the decision model and the prototype. So far, we applied the decision model to real-world data, but not in a full-fledged naturalistic setting including real people, tasks, and systems.

As for theoretical implications, our key contribution is a well-founded and validated decision model that tackles the exploration/exploitation trade-off. Building on mature descriptive OA knowledge (He and Wong 2004; Jansen et al. 2009; Gibson and Birkinshaw 2004; Tushman and O'Reilly 1996) as well as prescriptive VBM and PPM knowledge (Lehnert et al. 2016b, Linhart et al. 2015), the decision model adds to prescriptive OA knowledge. The decision model is the first to operationalize the structural OA approach and to tackle the exploration/exploitation trade-off analytically from a project portfolio selection and scheduling perspective. In particular, the decision model complements the work of Pellegrinelli et al. (2015), who chose a longitudinal case-based design to understand how OA can be achieved through projects and programs. While Pellegrinelli et al. (2015) analyzed the business transformation program of a European retail bank over about three years, our decision model does not only compile the manifold effects of exploration and exploitation projects in an analytically traceable manner, but also support the determination of the value-maximizing project portfolio. Further, the decision model is the first to integrate the outcome and behavioral perspective of OA by prioritizing investments in exploration and exploitation. Earlier research focused exclusively on the outcome perspective, e.g. by investigating effects of exploration and exploitation on operational performance (He and Wong 2004; Jansen et al. 2009), or on the behavioural perspective, e.g. by conceptually linking OA with dynamic capability theory to understand how OA works in practice (O'Reilly and Tushman 2008).

Fellow researchers can use the decision model's design specification and the prototypical instantiation as foundation for their own work. They can address the limitations of our decision model regarding the incorporation of stochastic project interactions, the explicit treatment of risks, and the ex-ante estimation of project effects. To do so, researchers can draw from knowledge related to stochastic optimization, simulation, and benefits management. Whenever extending the model, we recommend carefully deliberating for which limitations increased real-world fidelity justifies additional data collection effort and complexity. One must keep in mind that the decision model does not aim to estimate the real NPV of project portfolios, but to compare them based on a consistent calculation logic. As for limitations related to the decision model's evaluation, future research should seek the feedback of further experts – specifically from hitherto uncovered industries and small organizations. Such feedback will provide insights into the model's understandability and real-world fidelity. Future research should also apply the decision model in real-world settings to gain insights into usefulness and applicability. Further case studies will help identify how the decision model should be tailored to different organizational contexts. In the long run, these insights may set the scene for developing a design theory related to the exploration/exploitation trade-off. Another worthwhile endeavor is the development of a knowledge base related to OA decision-making. Such a knowledge base should be co-created by researchers and practitioners, including case descriptions and benchmarking data as well as guidelines and good practices for data collection. Beyond addressing limitations, future research may further develop the software prototype. For example, the prototype requires more advanced visualization, scenario, and sensitivity analysis functionality. Finally, future research should investigate how sensing and seizing capabilities can be incorporated, accounting for the fact that these capabilities can be developed over time as well.

As for managerial implications, our decision model provides decision-makers with a structured overview of criteria that influence the prioritization of exploration and exploitation – including relations among these criteria. Addressing the exploration/exploitation trade-off is a non-trivial endeavor that needs continuous attention as interdependent effects of projects on various performance criteria must be balanced over time. These insights facilitate informed discussions among decision-makers on the most appropriate way to implement OA in specific contexts. Business development and strategy departments as well as program managers can use the design specification of our model as a blueprint for deriving organization-specific solutions and extending their own methods. When applying the decision model, decision-makers can use the hints and potential data sources listed in the prototype application. In its current form, the decision model can be applied best in medium-sized and large organizations operating in dynamic business environments that dispose of mature PPM and performance management capabilities and have sufficient capacity to collect the required input data.

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Appendix 1. Overview of mathematical variables

Table A-1. Overview of mathematical variables

Project layer	
$\mathrm{EXPLORE\_COMP}_y$	Exploration projects implemented until period y
$\mathrm{EXPLOIT\_COMP}_y$	Exploitation projects implemented until period y
$\mathrm{EXPLORE\_RUN}_y$	Exploration projects currently running in period y
$\mathrm{EXPLOIT\_RUN}_y$	Exploitation projects currently running in period y
$a_j \in \mathbb{R}^+$	Relative effect $a_j \in]0;\infty[$ on the innovation degree. It equals $a_j \in]1;\infty[$, if an exploration project j has been finished in period $y-1$. Otherwise, it equals δ.
$\delta \in]0;1]$	Degeneration effect on innovation degree
$b_j - c_j \in \mathbb{R}^+$	Relative effects of exploration projects with $j \in \mathrm{EXPLORE\_COMP}_{y-1}$
$d_j \in]0;1]$	Relative effect $d_j \in]0;1]$ on the cumulated demand. It equals $d_j = 1$, if no exploration project j has been finished in period y. Otherwise, it equals $d_j \in]0;1[$.
$e_j - h_j \in \mathbb{R}^+; k_j - p_j \in \mathbb{R}^+$	Relative effects of exploitation projects with $j \in \mathrm{EXPLOIT\_COMP}_{y-1}$
Behavioral layer	
$N_y \in]0;1]$	Nonroutine ratio in period y
$M_y \in]0;1]$	Mandatory task ratio in period y
$F_y^{\text{change}} \in]0;1]$	Flexibility-to-change level in period y
$F_y^{\text{use}} \in]0;1]$	Flexibility-to-use level in period y
Outcome layer	
$NPV_r \in \mathbb{R}$	Risk-adjusted expected NPV of a distinct project portfolio r
$r \in R$	A distinct project portfolio from the set of admissible portfolios R
$r^* \in R$	The optimal project portfolio from the set of admissible portfolios R
$y \leq Y \in \mathbb{N}$	Period within planning horizon Y
$z \in \mathbb{R}_0^+$	Risk-adjusted interest rate
$t_y \in \mathbb{R}^+$	Average total processing time in period y
t_y^{NR}	Processing time for nonroutine operations in period y
Δt_y^{NR}	Additional time for nonroutine operations in period y
t_y^{R}	Processing time for routine operations in period y
$q_y \in \mathbb{R}^+$	Average total quality in period y
q_y^{NR}	Quality of nonroutine operations in period y
q_y^{R}	Quality of routine operations in period y
$q^{\max} \in \mathbb{R}^+$	Upper quality boundary
$i_y \in \mathbb{R}^+$	Innovation degree in period y
$CF_y^{\text{per}} \in \mathbb{R}$	Periodic cash flows in period y
$CF_y^{\text{op}} \in \mathbb{R}$	Operating cash flows in period y
$O_y^{\text{op}} \in \mathbb{R}^+$	Average total operating outflows in period y
$O_y^{\text{op,NR}}$	Operating outflows for nonroutine operations in period y
$\Delta O_y^{\text{op,NR}}$	Additional operating outflows for nonroutine operations in period y
$O_y^{\text{op,R}}$	Operating outflows for routine operations in period y
$O_y^{\text{inv}} \in \mathbb{R}^+$	Investment outflows in period y
$O_y^{\text{fix}} \in \mathbb{R}^+$	Fixed outflows in period y
$O_y^{\text{fix,NR}}$	Fixed outflows for nonroutine operations
$O_y^{\text{fix,R}}$	Fixed outflows for routine operations
$n(t_y, q_y, i_y) \in \mathbb{R}^+$	Expected demand in period y
$E_y \in]0;1[$	Experience curve effect in period y
CD_y	Cumulated demand up to period y considering the demand of all prior periods and the respective relative effects $d_y \in]0;1]$ for each period y
$\alpha \in]0;1]$	Constant elasticity used for the calculation of experience curve effects
$p \in \mathbb{R}^+$	Sales price of operations output

Appendix 2. Overview of the interviewed industry expert

Table A-2. Overview of the interviewed industry experts

ID	Current position / job title	Work experience (in years)	Academic background	Industry	Employees	Annual revenue
1	Project manager for agile transformation	>25	Mechanical engineering	Production – Power tools	19,000 (2015)	EUR 4.2 billion (2015)
2	IT project manager for innovation systems	>10	Business administration and information systems	Production – Automotive	122,000 (2015)	EUR 2.2 billion (2015)
3	Head of project management office for technology integration	>15	Business administration	Service – Telco	14,000 (2016)	EUR 0.6 billion (2015)
4	Senior sales manager for TV solutions	>25	Electrical engineering	Service – Telco	170,000 (2015)	USD 0.8 billion (2015)
5	Head of discount negotiation commercial roaming	>20	Business administration	Service – Telco	225,000 (2015)	EUR 9.2 billion (2015)
6	Vice president for content distribution	>20	Electrical, electronics, and communications engineering	Service – Internet provider	1,200 (2014)	EUR 1.9 billion (2014)
7	Director for digital transformation	>20	Business administration	Service – Banking	100,000 (2015)	EUR 3.5 billion (2015)
8	Principle innovation consulting	>25	Business administration	Production – Electrical manufacturing	350,000 (2015)	EUR 5.6 billion (2015)

Appendix 3. Highlights from the expert interviews

Table A-3. Highlights from the expert interviews

Topic	Comment	Implications
Project portfolio selection and scheduling	▪ Organizations must define trigger points for the repeated application of the decision model to ensure that once-estimated parameters are reviewed and updated (ID1, ID3, ID4).	Section 4.1: Hint added that the decision model should be applied repeatedly.
	▪ It is important to reassess project effects when re-applying the decision model due to internal or external changes to cope with planning uncertainty (ID2, ID8).	Section 4.1: Hint added that input parameters should be critically challenged when re-applying the decision model.
	▪ PPM depends on the capability to cancel projects that have become obsolete or are not successful. Otherwise, organizations will suffer from capacity overload (ID1).	Section 4.1: Hint added that projects can be cancelled or dropped when re-applying the decision model.
Decision model in general	▪ The innovation degree is crucial, but hard to operationalize in terms of performance indicators (ID3, ID5, ID7).	Appendix 4: Hint added on how to operationalize the innovation degree.
	▪ Demand is driven by quality, time, and innovation degree. Nevertheless, in industry settings, it is impossible to determine the demand unambiguously because of effects resulting from unpredictable customer behaviour or markets conditions (ID4, ID6).	Appendix 4: Hint added on how to estimate demand.
Exploration and exploitation projects	▪ It is impossible to estimate the effects of disruptive innovation. To overcome this difficulty, organizations should define a dedicated budget not associated with cash inflow expectations (ID4, ID7, ID8).	Section 4.3: Mentioned that the decision model focuses on incremental and radical innovation. Disruptive innovation is out-of-scope.
	▪ Launching an innovation does not only cause one-time investments, but also entails follow-up outflows (ID3, ID7).	Section 4.5: Effect is covered by the decision model. It also covers the partial destruction of experience curve effects due to exploration.
	▪ Technological innovations are important to enable operational efficiency. As they only affect internal operations without being visible to customers, they should be treated as exploitation projects (ID6, ID8).	Section 4.3: It covers that innovative technologies can be used for exploration and exploitation, not only for product innovation visible to customers.

Appendix 4. Detailed description of prototype application

In this section, we provide a detailed description of the prototype application. To apply the prototype, which implements the decision model presented in the manuscript, to real-world data, we chose one of the industry experts who had participated in the interviews. The expert was working in the telecommunications industry. In line with his background, our case company is a telecommunication provider, whose operations include activities such as contract preparation, service provision, and hotline support. As required for the prototype application, the expert provided us with input data for current operations, planned projects, and the general setting. Owing to confidentiality, we had to anonymize and slightly modify the input parameters. However, the principle relations still hold.

Operations data had to be collected from different sources, e.g. quality management, innovation management, workflow management, sales management, and customer relationship management systems. In detail, data on operational characteristics, economic indicators, and performance criteria for time, quality, and innovation degree could be retrieved from enterprise systems. However, values for the company's transforming capabilities depended on the expert's qualitative assessments. The same held true for the demand. While the periodic demand could be retrieved from the company's sales management system, its dependency on quality, time, and innovation degree had to be estimated. The procedure of data collection for operations data is explained below, while all results are summarized in Table A-4.

For assessing operational characteristics, i.e. nonroutine and mandatory task ratio, process models were analyzed. The analysis revealed that 20% of all operations are nonroutine operations, while 80% of these nonroutine operations can be covered by routine tasks. The transforming capabilities were set to 90% based on the expert's assessment. A value of 100% would imply that the company's employees had no superior skills in change and project management. Due to recent trainings, the human resources department estimated that transforming capabilities have substantial potential to be further improved.

Performance indicators for time, quality, and innovation degree were retrieved from enterprise systems and validated by the quality and innovation management departments. Time is operationalized as the time necessary to provide the service after signing a contract. It splits into time for routine operations and additional time for nonroutine operations. Quality is expressed in terms of customer satisfaction with the offered services' scope and availability, while the quality for routine operations is higher than for nonroutine operations. The innovation degree was measured as the ratio between innovations introduced over the last four periods in relation to innovations introduced by main competitors. For example, if organization 1 introduced three innovations over the last the three years, and the main competitors, that is, organizations 2 and 3, introduced four innovations, the innovation degree of organization 1 is 75%. If the telecommunication provider focuses too much on exploitation and does not invest in the innovative services, the innovation degree decreases by 5%.

Economic indicators for operating and fixed outflows as well as the price were also retrieved from enterprise systems and validated by the sales and financial department. Operating outflows for routine operations were set to 300 EUR, while 90 EUR come on top for nonroutine operations. Moreover, operating outflows for routine operations can be reduced by an experience curve effect of 0.005. Customers had to pay a fixed service fee of EUR 540 per period. The demand function depends on several components. About 60% of the case company's customers, i.e. 1.1 million core customers, were not affected by changes in time, quality, and innovation degree. The remaining 40%, i.e. 0.7 million customers, are strongly affected by the innovation degree, followed by quality and time. The expert indicated that this demand function is typical for the telecommunications industry.

Table A-4. Input parameters of the prototype application (operations data)

Operational characteristics	Nonroutine ratio $\boldsymbol{N_y}$	20%
	Mandatory task ratio M_y	80%
Transforming capabilities	Flexibility-to-use F_y^{use}	90%
	Flexibility-to-change F_y^{change}	90%
Performance indicators	Additional time for nonroutine operation Δt_y^{NR}	3 days
	Processing time of routine operation t_y^{R}	8 days
	Quality of nonroutine operations q_y^{NR}	70%
	Quality of routine operations q_y^{R}	75%
	Innovation degree i_y	85%
	Degeneration effect δ	5%
Economic indicators	Add. operating outflows of nonroutine operations $O_y^{\text{op,NR}}$	EUR 90
	Operating outflows of routine operations $O_y^{\text{op,R}}$	EUR 300
	Fixed outflows O_y^{fix}	EUR 250 million
	Price p	EUR 540
	Elasticity for experience curve effect α	0.005
Demand function	$n = 1{,}100{,}000 + 700{,}000 \cdot (0.3 \cdot \ln q + 1.5 \cdot \ln i \ + e^{1/t})$	
	Cumulated demand CD_0 for experience curve effect E_y	1.6 million

Project data were estimated by the expert together with some of the case company's experienced project managers based on data from the company's project management system and experience from past projects. Estimating the performance effects of all projects was the most challenging part of data collection. To account for estimation inaccuracies, we included optimistic and pessimistic effects. All projects are briefly introduced in Table A-5 and a summary of all project effects can be found in Table A-6.

Table A-5. Overview of exploration and exploitation projects in focus

Project ID	Project type	Description and project effects	Investment outflows
(1)	Exploitation project	*Expansion of the network infrastructure* Increases quality of routine and nonroutine operations, increases operating outflows for routine and additional operating outflows for nonroutine operations, and increases fixed outflows for routine operations	EUR 8.5 million
(2)	Exploitation project	*Modularization of service delivery* Reduces nonroutine ratio	EUR 1.2 million
(3)	Exploitation project	*Improving IT Infrastructure* Reduces operating outflows for routine and additional operating outflows for nonroutine	EUR 10.8 million

		operations, and reduces fixed outflows for routine operations	
(4)	Exploration project	*Training in agile methods and project management skills* Improves flexibility-to-use and flexibility-to-change	EUR 2.8 million
(5)	Exploration project	*Introduction of a service feature* Increases innovation degree and destroys cumulated demand	EUR 4.5 million
(6)	Exploration project	*Introduction of a next-generation service* Increases innovation degree and destroys cumulated demand	EUR 9.5 million

Table A-6. Input parameters of the prototype application (project data)

Project ID	**Project effects on**	**Opt.**	**Pess.**
(1)	Quality of routine operations q_y^{R}	1.15	1.1
	Quality of nonroutine operations q_y^{NR}	1.15	1.1
	Operating outflows of routine operations $O_y^{\mathrm{op,R}}$	1.002	1.0025
	Add. operating outflows of nonroutine operations $O_y^{\mathrm{op,NR}}$	1.002	1.0025
	Fixed outflows for routine operations $O_y^{\mathrm{fix,R}}$	1.001	1.0013
(2)	NR ratio N_{y}	0.9	0.95
(3)	Operating outflows for routine operations $O_y^{\mathrm{op,R}}$	0.988	0.991
	Add. operating outflows of nonroutine operations $O_y^{\mathrm{op,NR}}$	0.985	0.99
	Fixed outflows for routine operations $O_y^{\mathrm{fix,R}}$	0.991	0.992
(4)	Flexibility-to-use F_y^{use}	0.9	0.95
	Flexibility-to-change F_y^{change}	0.95	0.97
(5)	Innovation degree i_y	0.99	0.98
	Effect d_j on cumulated demand CD_{y-1}	0.3	0.25
(6)	Innovation degree i_y	1.01	0.99
	Effect d_j on cumulated demand CD_{y-1}	0.2	0.1

Finally, general data had to be taken from the case company's corporate decision-making policies. In the case at hand, one period lasted six months. We analyzed a planning horizon of six periods, where projects could be implemented in the first four periods. As we aimed to interpret the results of the decision model's application content-wise, we restricted the analysis to some projects and planning periods. Calculating the risk-adjusted expected NPV based on six periods is necessary to account for payback periods of late and future-oriented projects. The risk-adjusted interest rate was set to 2.5% per period. Further, the total investment budget was limited to EUR 30 million, and the maximum number of projects per period was set to two due to scarce resources, e.g. a limited number of project managers.

Based on the data, we used the prototype to determine all admissible project portfolios and calculated their value contribution in line with the decision model's objective function and all equations mentioned in the manuscript. Together with the industry expert, we defined six relevant scenarios. Our reference is scenario (A), which we outlined above. This scenario required checking about 9.500 project portfolios. In scenarios (B) to (F), we varied individual input parameters, i.e. a shorter planning horizon (B), a lower investment budget (C), a mandatory project (D), lower innovation degree (E), and a lack of transforming capabilities (F). For each scenario, we determined the optimal and worst project portfolios, while accounting for optimistic (opt.) and pessimistic (pess.) effects. Below, we discuss the results of scenario (A) in detail and provide an overview of the results related to the other scenarios. The results are shown in Table A-7.

Table A-7. Optimal and worst project portfolios from the scenario analysis

		Optimal project portfolio	**Worst project portfolio**
(A) General case	Opt.	({2,3}, {6}, {5}, { }) EUR 911.92 million	({ }, { }, {4}, {3}) EUR 762.13 million
	Pess.	({1,3}, {2,4}, { }, { }) EUR 886.81 million	({ }, {4}, {1}, {5,6}) EUR 750.11 million
(B) Planning horizon (two periods only)	Opt.	({1,3}, {2,4}) EUR 642.07 million	({4}, {1}) EUR 567.61 million
	Pess.	({1,3}, {2,4}) EUR 631.52 million	({4}, {5,6}) EUR 555.55 million
(C) Budget restriction (EUR 20 million)	Opt.	({6}, {1,2}, { }, { }) EUR 882.72 million	({ }, { }, {4}, {3}) EUR 762.13 million
	Pess.	({2,3}, {1}, { }, { }) EUR 856.79 million	({ }, { }, {4}, {5,6}) EUR 751.01 million
(D) Mandatory project (project 5 in period 2)	Opt.	({1,4}, {5}, {6}, { }) EUR 901.53 million	({ }, {5,6}, {4}, { }) EUR 788.41 million
	Pess.	({1,2}, {5}, {6}, { }) EUR 864.3 million	({ }, {5,6}, {4}, {1}) EUR 754.47 million
(E) Innovation degree $(\boldsymbol{i_y = 0.5})$	Opt.	({6}, {1,2}, {5}, { }) EUR 121.54 million	({ }, { }, {4}, {3}) EUR -26.32 million
	Pess.	({1,3}, {2,4}, { }, { }) EUR 96.10 million	({ }, {4}, {3}, {5,6}) EUR -33.28 million
(F) Transforming capabilities $(\boldsymbol{F_y^{\text{change}} = 1, F_y^{\text{use}} = 1})$	Opt.	({2,3}, {6}, {5}, { }) EUR 907.99 million	({ }, { }, {4}, {3}) EUR 759.5 million
	Pess.	({1,3}, {2,4}, { }, { }) EUR 883.09 million	({ }, {4}, {1}, {5,6}) EUR 746.36 million

Notation: ({2,3}, {6}, {5}, { }) denotes a planning horizon of four periods, whereby project (2) and (3) have been scheduled for period 1, project 6 for period 2, project 5 for period 3, and no project for period 4.

Regarding the optimistic effects in scenario (A)**,** the optimal portfolio includes two exploration and two exploitation projects, i.e. projects (2), (3), (5), and (6), scheduled over four periods. Projects (2) and (3) are scheduled for period 1, project (6) for period 2, and project (5) for period 3. No project is scheduled for period 4. The implementation of these projects will lead to a value contribution of about EUR 910 million. The worst portfolio comprises two projects, i.e. projects (4) and (3), scheduled for the latest possible periods. The value contribution of the worst portfolio is 16 % lower than that of the optimal portfolio, which is worse than implementing no projects at all. In the optimal case, projects (2) and (3), i.e. both exploitation projects, are scheduled early. This is because project (2) reduces the NR ratio, an effect that improves operational performance with respect to time and quality. Both projects also reduce the operating and fixed outflows. Both exploration projects are scheduled to late periods. This is sensible as they are required to meet the customers' expectations regarding innovation and to prevent a very high degeneration effect, which would occur if the company did not introduce new services.

As the other scenarios differ only slightly from the reference case, we restrict our discussion to the most significant changes. Scenario (B) illustrates that a shorter planning horizon shifts the focus on the short-term effects of exploitation projects. In scenario (C), the worst project portfolio based on pessimistic estimations corroborates that an extreme exploration focus it not sensible as innovations do not outweigh efficient operations. Scenario (D) shows that tighter restrictions, which become manifest in a mandatory project and a fixed period, typically lead to a lower value contribution – even if the same projects are selected. As shown in scenario (E), the innovation success of an organization strongly depends on its competitors' innovativeness. Finally, scenario (F) underlines the importance of developing long-term oriented transforming capabilities. An analysis of the optimal project portfolios across all scenarios reveals that, in the case at hand, portfolios including both exploration and exploitation projects lead to higher value contributions compared to portfolios that include only exploration or exploitation projects.