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Modeling project criticality in IT project portfolios

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Abstract

Today's IT project portfolios (ITPP) contain many projects and varied interdependencies. Depending on a project's criticality to the ITPP, a failure can have massive consequences. However, existing methods usually only assess overall project portfolio risk and do not account for the criticality of single projects and their dependencies. Applying Bayesian network modeling to ITPPs, we bridge this gap and extend the current body of knowledge for the information systems and project management literatures. Our new method analyzes single projects' criticality in a portfolio context by considering both transitive dependencies and different dependency types in an integrated way. Since we demonstrate that single projects' criticality can vary substantially, being aware of which projects are critical is a key success factor for ITPP management. For practitioners, our method provides a straightforward procedure to enhance ITPP risk management.

Keywords: IT project portfolio management; IT project criticality; Bayesian network; Interdependencies

1. Introduction

With hundreds of projects and a multitude of interdependencies, today's large and complex IT project portfolios (ITPPs) are best described as IT project networks. Owing to strong dependencies between projects in a portfolio, the failure of only one project can lead to cascading effects that impact an entire ITPP, in the worst case. In another case, the failure of a different project may barely affect an ITPP at all. Thus, the network-like complexity and the resulting effects cannot be overseen or anticipated by project or project portfolio managers alone, but must be met using analytical methods that address the single project in the portfolio context.

What makes ITPPs so very complex is so-called transitive dependencies (Beer et al., 2015; Wolf, 2015). Generally speaking, *transitive dependencies* describe situations where A depends on B, B depends on C and then A depends on C (Huang and Song, 2007), although A does not necessarily have a direct dependency on C. Thus, projects can only have transitive dependencies if there are three or more projects. Imagine three projects, where project A depends on project B, which is a direct dependency. Also, project B depends on project C, which is a direct dependency, too. In addition, project A now depends transitively (over project B) on project C as well. Thus, a failure of project C would impact not only project B, caused by the direct dependency, but also project A, caused by a transitive dependency. Regarding IT projects, various dependency types should be considered from an ITPP management perspective. Most authors distinguish between resource dependencies, technical dependencies, and dependencies regarding benefits (e.g. Lee and Kim, 2001; Santhanam and Kyparisis, 1996; Tillquist et al., 2002; Zuluaga et al., 2007). While resource dependencies originate from shared resources between different projects, technical dependencies arise when multiple IT projects require the output of a predecessor IT project (Bardhan et al., 2004; Müller et al., 2015). A predecessor project that fails to deliver the intended (technical) output may cause serious issues

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for dependent projects. Also, a project in the ITPP may over-use shared resources, which may lead to a shortage of resources for multiple other projects and can even lead to a failure of an entire ITPP (Heinrich et al., 2014). In contrast, benefit dependencies occur if one project benefits from other projects' success. Thus, benefit dependencies contribute positively to a portfolio, while resource and technical dependencies incorporate risk accumulation effects.

Project success or failure is often linked to three key objectives: time, budget, and quality (Wit, 1988). However, the criteria for project success or failure are ambiguous in both the literature (cf. Atkinson, 1999) and in practice, and many other success criteria have recently been added (Aga et al., 2016). Particularly for IT projects, Flyvbjerg and Budzier (2011) note that one out of six IT projects has an average cost overrun of 200% and an average schedule overrun of almost 70%. In 2015, the Standish Group reported that 66% of technology projects at least partially fail in terms of time, budget, or scope (Standish Group, 2015). To date, there have been no studies into how many of these failures are caused by failures of other projects in the same ITPP. However, chances are that a reasonable portion of failures is at least partly caused by dependency structures between projects and unforeseen (or unforeseeable) cascading effects. This is in line with recent studies that indicate that IT project risk management is regularly under-performed in practice (Bannerman, 2008; Kutsch et al., 2014). Most common risk assessment approaches focus on standalone IT project risk assessment, and do not consider dependencies (de Bakker et al., 2010; Bardhan et al., 2004; Jonen and Lingnau, 2007), although dependencies further raise the impacts of risks (Buhl, 2012; Centeno et al., 2015; Graves et al., 2003; Martínez and Fernandez-Rodriguez, 2015). While the ITPP management literature emphasizes the insufficiency of existing ITPP risk assessment methods and the need for an adequate consideration of dependencies (Flyvbjerg and Budzier, 2011; Müller et al., 2015), very few approaches have incorporated (transitive) dependencies in ITPP risk assessment.

The larger an ITPP, the higher the risk is that a single project's failure threatens all other projects in a portfolio. To explain this phenomenon, the financial literature has come up with the notion of *too big to fail* and *too interconnected to fail* (Markose et al., 2012), particularly looking back to the financial crisis that began in 2008. In the context of ITPP management, the notion of criticality is usually used to describe the same situation (Beer et al., 2015; Wolf, 2015). A project can be regarded as riskier “the more critical it is, i.e., the more of its rather important activities are rather critical” (Kuchta, 2001, p. 305). In line with Wolf (2015) and Beer et al. (2015), we transfer the concept of criticality to the project portfolio level and consider a project to be more critical when it is more critical for the ITPP's success.

One approach to tackle complex dependency structures in networks is to use probabilistic graphical models (Jensen et al., 2007; Koller and Friedman, 2009). Especially Bayesian network modeling has been widely used to analyze and assess cascading effects in other research fields (Garvey et al., 2015; Khakzad et al., 2013; Marsh and Bearfield, 2004; Ren et al., 2009; Shenoy and Shenoy, 1999; Trucco et al., 2008). Bayesian network modeling provides the possibility to analyze the impacts of single projects and their dependencies in a portfolio context. Thus, we examine Bayesian network modeling as an approach to address IT projects' criticality in a portfolio context. By doing so, we aim at providing a method which overcomes the main drawbacks of existing approaches. Further, we want to point out the importance of regarding projects as part of an interdependent project portfolio, not as isolated items. Our research question is:

How can the criticality of single IT projects in interdependent ITPPs be analyzed and assessed using a Bayesian network modeling approach?

To address this question, we follow the research cycle of Meredith et al. (1989), who state that “all research investigations involve a continuous, repetitive cycle of description, explanation, and testing” (Meredith et al., 1989, p. 301). For the description phase, which documents and characterizes the subject of interest, we outline the theoretical background on the failure, success, and criticality of IT projects in ITPPs and the current state of methods for analyzing complex dependency structures in ITPPs. As the situation's dynamics may be captured in the explanation phase, we elaborate on the procedure of assessing criticality using Bayesian network modeling for ITPPs. Finally, in a first step towards the testing phase, we test our model's usability with an application example. To study the model's behavior and to test its robustness to the deviation of input parameters, we conduct a sensitivity analysis and use simulation as a dominant testing mode (Meredith et al., 1989; Pannell, 1997). Finally, we summarize results, discuss limitations, and provide avenues for future research.

2. Theoretical background

2.1. Status quo of methods in IT project portfolio management and project criticality

Many approaches in ITPP management consider the overall risk of an ITPP to balance risk and return. (McFarlan, 1981) was the first to address portfolio management in the context of Information Systems (IS). Since then, many methods for ITPP management have been developed. Starting from pure project evaluation or selection methods such as diverse scoring models (Lucas and Moore, 1976; Walter and Spitta, 2004), applications of the balanced scorecard (van Grembergen, 2005), or earned value methods for continuous project steering (Anbari, 2003), IT project management and evaluation methods have evolved to IT project portfolio methods over time. For a detailed overview, we refer to Reyck et al. (2005), who provide a historical and thematic outline. While approaches such as linear programming (Ghasemzadeh and Archer, 2000) or goal programming (Lee and Kim, 2001) have been developed to provide decision support in finding an optimal project portfolio, they usually neglect the specifics of IT project portfolios (Ullrich, 2013), such as transitive interdependencies. Further, multiple approaches for project and multi-project planning exist (Hans et al., 2007) that incorporate aspects of uncertainty, deal with the question of sharing scarce resources (Laslo, 2010; Lova et al., 2000), or both (Laslo and Goldberg, 2008).

The ITPP management literature also provides methods to assess ITPPs incorporation of dependencies between projects (Liesiö et al., 2008; Wiley et al., 1998) or resources in optimization models (Kundisch and Meier, 2011a; Lee and Kim, 2001; Meier et al., 2016; Santhanam and Kyparisis, 1996). Other approaches use the portfolio theory of Markowitz (1952) and transfer the approach to ITPP management (Beer et al., 2013; Butler et al., 1999; Wehrmann et al., 2006) or draw on real options (Bardhan et al., 2004; Benaroch and Kauffman, 1999; Pendharkar, 2010, 2014). However, all these methods either look at interaction effects between single projects or a set of projects, solve specific capacity problems (Beer et al., 2015), or allow for the optimization of an overall project portfolio. It is important to mention that several of the aforementioned approaches allow for the incorporation of direct dependencies between many different projects. However, that is not to be confused with transitive dependencies.

While all these approaches provide valuable insights, neither explicitly considers transitive dependencies' effects at a project portfolio level, nor accounts for the specifics a network-like structure (caused by the dependencies) can have. In particular, besides the overall risk of an ITPP, ITPP management must be aware of the riskiness of projects to the ITPP. Projects might not be risky on their own (or only have little direct dependencies to other projects) but might cause severe damage to the entire ITPP as their transitive dependencies might lead to cascading failure of other projects. Thus, we propose to consider a project's *criticality* in an ITPP that incorporates (transitive) dependencies between all projects in the portfolio, in addition to the overall risk of an ITPP.

Criticality is mostly used in the context of project scheduling and critical path analysis (Chen and Huang, 2007; Kuchta, 2001; Williams, 1992). In this context, projects are regarded as more critical when more activities are critical in terms of delays (Chen and Huang, 2007; Kuchta, 2001). The concept of criticality has already been transferred to the ITPP context (Beer et al., 2015; Wolf, 2015). In this context, a project can be regarded as more critical when it is more critical to the success of the portfolio or the organization (Beer et al., 2015; Howell et al., 2010; Wolf, 2015). Notably, a general definition of IT projects' success or failure does not exist, and we advise against a general definition. We refrain from providing a specific definition of project success or failure; instead, we encourage the use of organization-specific and context-specific definitions and refer to the literatures.

While there are different classifications of dependencies, Beer et al. (2015) note that authors often distinguish between "resource dependencies, technical dependencies or dependencies regarding benefits" (e.g. Lee and Kim, 2001; Santhanam and Kyparisis, 1996; Tillquist et al., 2002; Zuluaga et al., 2007). Other and more detailed classification schemes for dependencies can be found for instance in Wehrmann et al. (2006), Kundisch and Meier (2011b), and Müller et al. (2015). Since we focus on providing a method for criticality analysis in complex ITPPs that incorporates the key dependencies, we stick to the interpretation of Beer et al. (2015), focusing on resource and technical dependencies. While resource dependencies arise from shared personal or shared infrastructure between projects, technical dependencies arise when an IT project requires the output of its predecessor IT project (Beer et al., 2015; Diepold et al.), that might be functionalities or data output. With their specific properties, both resource and technical dependencies can cause cascading effects in ITPPs. In particular, to address the complex dependency structure, we take up the network interpretation of ITPPs (Beer et al., 2015; Wolf, 2015). Network measures have been proven suitable to quantitatively analyze interactions and dependency patterns in networks (Newman, 2013). For instance, *betweenness centrality*, *closeness centrality*, and *alpha centrality* are widely used in social network analysis (Bonacich and Lloyd, 2001; Freeman, 1977; Wasserman and Faust, 2009). Wolf (2015) uses alpha centrality to assess IT projects' criticality in an ITPP. Beer et al. (2015) extend this method via an ad hoc approach and apply alpha centrality to integrate indirect dependencies' effects into a measure of risk for ITPP evaluation. Radszuwill and Fridgen (2017) compare the positive and negative effects of resource interactions in ITPPs based on alpha centrality. However, we lack approaches that assess the criticality of single projects in a portfolio and incorporate different dependency types.

3. A Bayesian network approach for criticality analysis in complex ITPPs

Bayesian networks, also called belief networks, have been widely used as a suitable method for project management and risk assessment (Marsh and Bearfield, 2004; Martínez and Fernandez-Rodriguez, 2015; Ren et al., 2009; Shenoy and Shenoy, 1999; Shenoy and Shenoy, 2002; Trucco et al., 2008). For instance, Khakzad and Reniers (2015) apply a Bayesian network methodology for risk assessment in highly vulnerable process plants. Garvey et al. (2015) use a Bayesian network approach to develop a model of risk propagation in a supply network. Some authors have also transferred the use of Bayesian networks to IT project management (Gingnell et al., 2014; Hu et al., 2012; Hu et al., 2013; Khodakarami and Abdi, 2014; Lee et al., 2009). The application of Bayesian network modeling is promising to overcome the outlined shortcomings of existing approaches. The impacts of single projects' failure in ITPPs as well as different and transitive dependencies can be addressed. By considering probabilities of failure, Bayesian networks also allow us to incorporate a notion of uncertainty. Further, our method allows us to account for the economic impacts of failure. Our approach is methodologically similar to the so-called *with-without* principle from risk management (Howe and Cochrane, 1993; Tasche, 2008), which calculates an asset's marginal risk contribution by calculating the difference of the portfolio risk with and without the asset (Howe and Cochrane, 1993; Tasche, 2008). Since it is not a realistic scenario for ITPPs to simply exclude projects, we adjust the principle slightly for our model, calling it *failed-not failed* principle: We use the difference between the cost of failure in the entire ITPP if project P_i fails and if it does not fail as our measure of risk.

3.1. Modeling IT project portfolios as Bayesian networks

A Bayesian network is a directed acyclic graph (DAG), with nodes representing a set of random variables and edges representing conditional dependencies between nodes (Jensen, 2002; Russell and Norvig, 2010). Thus, node X with direct edge to Y is called a *parent* of Y, and Y is called its *child*. Nodes without direct edges pointing to them are called *roots*. If a node X influences a node Z directly (through an edge) or indirectly (transitively through edges of neighboring nodes), then Z is a *reachable* node for X (Neapolitan, 2004). An edge indicating from node X to node Y implies that node X impacts node Y, i.e. node Y depends on node X.

We extend the modeling procedure of Beer et al. (2015) and Wolf (2015), modeling ITPPs as graphs as follows: IT projects and shared resources are depicted by nodes. Technical dependencies and resource dependencies are depicted by directed edges between projects and their shared resources. An edge indicating from node P_i to node P_j implies that project P_j depends on P_i. Fig. 1 illustrates a technical dependency of P_j on P_i. It reads: "project P_j depends on project P_i".

To distinguish resources and projects, we used circles to depict projects and squares to depict resources. We used dashed edges to represent resource dependencies, as opposed to solid edges for technical dependencies. Note that resources only assigned to a single IT project do not constitute a resource dependency, and we do not consider them as nodes in our model. Thus, we consider shared resources between projects as nodes with two or more resource dependencies originating from them. Resources are always roots, and the originating edges point to the projects that share the particular resource. Fig. 2 illustrates resource dependencies between IT projects P_i and P_j owing to the shared resource R_I. It reads: "project P_i (and project P_j) depends on resource R_I".

To model ITPPs as Bayesian networks, the corresponding graph must be a DAG. An acyclical graph requires it to be impossible to reach a node again that one started from, i.e. there are no cycles in the graph. Since we always model resources as roots, resources are always acyclical. Thus, we state Assumption 1 for technical dependencies:

Assumption 1. *The graph of an ITPP is acyclical for technical dependencies.*

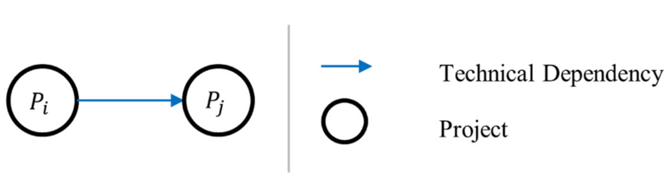

Fig. 1. Two IT projects with Technical Dependency.

This assumption is in line with real-world scenarios of IT projects without dual relationships between projects (cf. Wiest, 1981). We consider IT projects as fine-grained subprojects which only deliver one output; thus, technical dependencies do not cause a cyclical dependency.

Bayesian networks enable one to calculate probabilities of a certain event's occurrence, given particular observations of the state of a network's nodes (Neapolitan, 2004). In our model, each IT project or shared resource can have two states: success (T) or failure (F). As noted, since the definitions of success and failure are highly context-specific, we do not provide general definitions; instead, we hint at what a definition could look like in real-world applications. In our case, for instance, it is reasonable to consider an IT project as failed if it is unable to deliver the desired output in terms of quality or scope, or within a given time. A failure of shared resources occurs when a resource is over-used by one project and does not have the capacity to fulfill its tasks for other projects.

For the DAG in Fig. 2, with three nodes P_i, P_j, and R_I, we obtain the probability of an event's occurrence (e.g. the success of P_i, $P_i = T$), given an observation (e.g. failure of R_I, $R_I = F$) in the network as in Eq. (1).

$$P(P_i = T | R_I = F) = \frac{P(P_i = T, R_I = F)}{P(R_I = F)} = \frac{\sum_{P_j \in \{T,F\}} P\left(P_i = T, R_I = F, P_j\right)}{\sum_{P_i, P_j \in \{T,F\}} P\left(P_i, R_I = F, P_j\right)} \tag{1}$$

To build a Bayesian network, conditional probability tables (CPT) contain the strength of edges (conditional dependencies) between directly connected nodes (Jensen et al., 2007; Neapolitan, 2004), i.e. for a project P_j that depends on project P_i, the CPT contains the conditional probability of success (and failure) of project P_j, given success (or failure) of project P_i. For our modeling procedure, a root node's CPT contains the estimated values of probabilities of the node's success (T) and failure (F). A non-root node's CPT contains the estimated values of probabilities of the node's success and failure, given all possible combinations of the success and failure of its parents. That is, the CPT entries express the strength of the node's technical and resource dependencies in an integrated way. Thus, we do not distinguish between dependency types in the subsequent calculations, referring to the entries of CPTs instead.

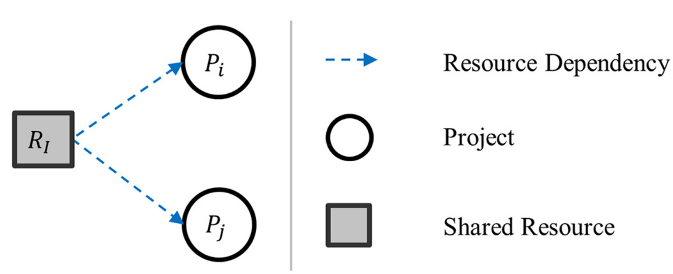

Fig. 2. Two IT Projects with Resource Dependency.

Common methods to estimate CPTs either use existing data or expert estimations (Khodakarami and Abdi, 2014; Neapolitan, 2004; Zhang et al., 2013). As usually data for CPTs is not available in ITPPs yet, we rely on expert estimations. However, the experts' estimations are prone to cognitive biases, like *anchoring* (Tversky and Kahneman, 1974) and psychological and political-economic biases, like *optimism bias* and *strategic misrepresentation* (Flyvbjerg, 2008). The biases can lead to substantial errors in the CPT estimation. To overcome estimation biases Jørgensen (2004) proposes to guide the expert with estimation principles, to support the estimation process, and to provide feedback and training opportunities. In estimating the CPT it is especially crucial to clearly define the probability of failure, since there are various perceptions of success (or failure) and (conditional) probability. To estimate CPTs, an expert estimates probabilities of success and failure of each project and shared resource, given all possible combinations of success and failure of their parents. For a small ITPP, one manager might be able to estimate all CPT entries. For large and complex ITPPs however, we require several managers to estimate the required values. In these cases, for instance, every IT project manager should provide the CPT of their IT project and its shared resources. This decentral data estimation approach benefits from the local information of all IT project managers. However, close collaboration with ITPP managers in the estimation process is crucial, to ensure data consistency across all experts. Notably, a generally applicable procedure to identify all entries of a CPT is a key task for future research, but exceeds the scope of this paper. As a first research step in this direction, i.e. to account for estimation errors, we provide a sensitivity analysis for the proposed approach.

3.2. Criticality assessment based on Bayesian network modeling

Bayesian networks enable the estimation of probabilities of success or failure of certain nodes (e.g., IT projects or shared resources), based on an observation with regard to other nodes (e.g., success or failure of an IT project) (Jensen, 2002). As the first step of our modeling, from the CPTs, we calculate the conditional probability of failure of each project P_j if project P_i fails: $P(P_j = F | P_i = \mathrm{F})$. Second, we calculate the conditional probability of failure of each project P_j if project P_i does not fail: $P(P_j = F | P_i = T)$. Then, we assess the criticality of P_i based on the changes this failure of P_i causes to the states of the other IT projects P_j. To consider the economic impacts, increase the results' tangibility, and provide managerial insights, we incorporate the *cost of failure (*CF*)* of IT projects into our assessment. We integrate the cost of failure by defining the *expected cost of failure (ECF)* of an IT project P_j as the product of the probability of its failure and its cost of failure using the deduced *failed-not failed* principle. We calculate the ECF as in Eq. (2).

$$ECF\left(P_j = F|P_i\right) = P\left(P_j = F|P_i = \mathrm{F}\right) \times CF\left(P_j\right) - P\left(P_j = F|P_i = T\right) \times CF\left(P_j\right) \quad (2)$$

The result of Eq. (2) is the effect that P_i has on the failure of its reachable project P_j. We define the set of reachable projects P_j from project P_i as $RP_{i,\,j}$. To calculate the *total cost of failure (TCF)* of P_i, we sum up the expected cost of failure of P_i and all its reachable IT projects P_j, as shown in Eq. (3).

$$TCF(P_i) = CF(P_i) + \sum_{j \in RP_{i,j}} ECF\left(P_j = F|P_i\right) \quad (3)$$

The result of Eq. (3) is the extent of loss that P_i can cause in the network. As a final step, we need to consider the probability of failure for P_i to incorporate the likelihood of this loss and provide the *risk exposure (RE)*, also called the risk impact of each IT project (Barki et al., 2001; Boehm, 1989). Eq. (4) provides the RE of P_i as an integrated cost-risk measure of criticality for the IT project P_i.

$$RE(P_i) = TCF(P_i) \times P(P_i = F) \quad (4)$$

By design, an IT project's RE is higher if its failure constitutes a higher impact for the network and if more IT projects may be affected by it. Also, an IT project's RE decreases with increasing IT project success probability, lowering the impacts of dependencies. Thus, our model enables us to consider both economic impacts of failure of single IT projects as well as the dependence structure of ITPP in a holistic approach to account for IT projects' criticality.

4. Application example and model analysis

4.1. Application example

Our model to assess IT projects' criticality in ITPPs can be placed in the explanation phase of the research cycle by Meredith et al. (1989). Further, we take first steps towards the testing phase, evaluate the functionality and usability of our model, and apply it to a real-world case. Our model is scalable and designed for large and complex ITPPs, where criticality can no longer be assessed intuitively. However, for demonstration purposes, we have deliberately chosen a relatively small ITPP to allow for comprehensibility. To gather data for the application example, we interviewed the IT manager of an application-oriented research organization with more than 200 employees in two branches (B1 and B2). We asked the IT manager to describe the organization's ITPP, the main dependencies, and the main challenges of the organization's IT department. The manager noted that most of its IT infrastructure is distributed to the cloud. Thus, the IT infrastructure is highly scalable, and resource dependencies due to infrastructure can be neglected. The organization conducts an ITPP that consists of eight projects (P_1–P_8), illustrated in Table 1. However, it has limited IT staff capacity. Thus, projects' resource dependencies mainly occur due to personnel resource-sharing. The IT manager identified staff sharing as its ITPP's primary challenge. One expert with in-depth know-how on all projects and the organization is involved in many projects; we depict this expert as R_1. This is the only shared resource of this ITPP; the other IT staff members each work on one project only.

Table 1
ITPP of the firm.

Variable	Description
P_1	System images (operating system 1) for B1's laptops
P_2	System images (operating system 1) for B1's workstations
P_3	System images (operating system 1) for B2's laptops (this branch has no workstations)
P_4	System images (operating system 2) for laptops (integrated solution for B1 and B2)
P_5	System images (operating system 2) for B1's workstations
P_6	System images (mobile operating system) for laptops, workstations, and other devices, which enables the bring-your-own-device concept and aims to release a portable operating system
P_7	Connection tool for improved usability of the corporate cloud platform on laptops and workstations
P_8	Connection tool for improved usability of corporate cloud platform on all systems
R_1	Personnel resources shared between projects

As the first step to apply our model, we sought to prepare the DAG for our ITPP. The IT project manager described the dependencies between the IT projects in the ITPP. P_1 and P_2 are conducted in parallel and share resource R_1. The IT project manager emphasized the importance of the successful implementation of P_1 and P_2 to reuse the developed functionalities for the successful implementation of P_3. Thus, P_3 technically depends on P_1 and P_2. P_4 and P_5 share R_1, which causes a resource dependency. P_4 and P_5 require the functionality of P_3, which causes a technical dependency to P_3. P_6 depends on the projects P_4 and P_5, since the availability of the submodules of the system image creation and the establishment of user acceptance for operating system 2 are necessary to start P_6. P_6 also depends on P_8 to assure its connectivity to the corporate cloud platform. P_7 can be started independently of other projects. However, P_7 needs to be successfully implemented so as to conduct P_8. Thus, we model a technical dependency between P_7 and P_8. Fig. 3 illustrates the ITPP's DAG.

Second, we require the data for the CPTs. As noted, for our relatively small ITPP, it is possible that an IT manager comes up with estimations for all projects. However, in larger project portfolios, different stakeholders are required to deliver this data, which may lead to the outlined biases, deviations, and distortions. For our ITPP, the IT manager estimated the

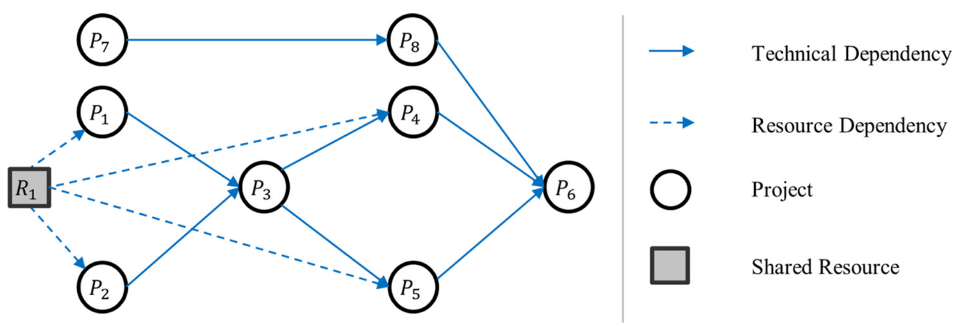

Fig. 3. ITPP of a medium-sized organization.

Table 2
Conditional probability tables (CPT) for all projects.

Project 1	$R_1 = F$				$R_1 = T$			
$P(P_1 = F \mid R_1)$	85%				5%			
Project 2	$R_1 = F$				$R_1 = T$			
$P(P_2 = F \mid R_1)$	95%				15%			
Project 3	$P_1 = F$				$P_1 = T$			
	$P_2 = F$		$P_2 = T$		$P_2 = F$		$P_2 = F$	
$P(P_3 = F \mid P_1, P_2)$	100%		95%		50%		10%	
Project 4	$R_1 = F$				$R_1 = T$			
	$P_3 = F$		$P_3 = T$		$P_3 = F$		$P_3 = T$	
$P(P_4 = F \mid R_1, P_3)$	100%		90%		85%		25%	
Project 5	$R_1 = F$				$R_1 = T$			
	$P_3 = F$		$P_3 = T$		$P_3 = F$		$R_1 = T$	
$P(P_5 = F \mid R_1, P_3)$	100%		90%		75%		30%	
Project 6	$P_8 = F$				$P_8 = T$			
	$P_4 = F$		$P_4 = T$		$P_4 = F$		$P_4 = T$	
	$P_5 = F$	$P_5 = T$	$P_5 = F$	$P_5 = T$	$P_5 = F$	$P_5 = T$	$P_5 = F$	$P_5 = T$
$P(P_6 = F \mid P_8, P_4, P_5)$	100%	100%	100%	50%	100%	100%	100%	40%
Project 7	$P(P_7 = F)$				$P(P_7 = T)$			
	10%				90%			
Project 8	$P_7 = F$				$P_7 = T$			
$P(P_8 = F \mid P_7)$	100%				20%			
Resource 1	$P(R_1 = F)$				$P(R_1 = T)$			
	30%				70%			

Table 3
Cost of failure (CF) for all projects.

Project	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
CF (€)	4375	5000	2500	625	1875	10,000	12,500	6250

conditional probabilities for project success and failure of all projects, given the success or failure of their parents. Table 2 provides an overview of the CPTs for all projects.

The project manager also estimated the cost of failure of each IT project ($CF(P_i)$). We depict the estimations in Table 3.

For demonstration purposes, we briefly elaborate on the computation path for $RE(P_3)$. Table 2 contains the conditional probabilities that a project fails if its parents fail. Using standard procedures for Bayesian networks, we can calculate the probability that a project P_j fails if another project P_i fails (or succeeds). We depict the probability $P(P_j = F|P_3 = F)$ and $P(P_j = F|P_3 = T)$ for all reachable projects of P_3 ($j = 4, 5, 6$) in Table 4. Using Eq. (2) and the $CF(P_j)$, we calculate the $ECF(P_j = F|P_3)$.

We use Eqs. (3) and (4) and obtain $TCF(P_3) = 6{,}197$€ and $RE(P_3) = 4{,}099$€ ($P(P_3 = F) = 66\%$). We proceed analogously for all projects in our ITPP and obtain the RE of each project, provided in Table 5.

We sort projects based on their RE, i.e. P_1 may be considered the most critical in terms of RE, P_4 may be considered the least critical. With the information at hand, we are able to assess the criticality of single IT projects in the ITPP. Since the RE between single projects only shows little differences in certain cases (e.g. P_1 and P_8) and big differences in others (e.g. P_2 and P_4), we suggest defining criticality thresholds that allow us to group projects based on their RE. Thus, an even more intuitive classification can be provided for project portfolio management. However, notably, such a classification must be derived from company-specific and portfolio-specific properties. Thus, we refrain from providing a generalizable classification scheme. For our example, we can group projects with similar REs and can assign them to priority groups as follows. System images (operating system 1) for B1's laptops and workstations (P_1 and P_2) and the connection tool for the improved usability of corporate cloud platform on all systems (P_8) belong to the category of *most critical IT projects*. Since their REs are very similar, for all three, high management attention is advised, to prevent their failure and thus to prevent large impacts on the ITPP. System images (operating system 1) for B2's laptops (P_3), mobile operating system project (P_6), and the connection tool for improved usability of corporate cloud platform on laptops and workstations (P_7) have lower REs and can be assigned to the category of *medium-risk projects* (category 2). Since the other projects contribute low RE, their impacts on the ITPP in terms of risk can be regarded as fairly small.

Table 4
Conditional probability of the failures of reachable IT projects from P_3.

IT project	$P(P_j = F|P_3 = F)$	$P(P_j = F|P_3 = T)$	$ECF(P_j = F|P_3)$.
P_4	73%	8%	403 €
P_5	80%	0.4%	1500 €
P_6	73%	55%	1794 €

Table 5
IT projects sorted based on their RE.

Project	P_1	P_8	P_2	P_3	P_6	P_7	P_5	P_4
RE (€)	6707	6611	6032	4099	3984	3823	2454	717

4.2. Sensitivity analysis

To analyze our model, we conducted a sensitivity analysis, for three reasons. First, it can provide deeper insights into the implications of the results. Second, since our method uses estimated parameters, it is particularly important to analyze the model behavior assuming estimation inaccuracies, i.e. given altered input parameters. Third, understanding the relationship between input parameters and criticality prioritization of projects in an ITPP are crucial as a first step towards a sound evaluation of the model. A simulation-based sensitivity analysis is a valid testing mode (Meredith et al., 1989) before larger real-world cases can be used for a method evaluation. Thus, we conducted a sensitivity analysis concerning the input data from the application example. In our model, the main factors of uncertainty are the conditional probabilities provided in the CPTs. Since the CF only contributes to the computation of RE as a constant factor (see Eqs. (2) and (3)), it causes no unexpected behaviors on the part of the results. Thus, we focused on the sensitivity analysis for conditional probabilities in our network. Since our model includes many conditional probabilities, we analyzed it in two ways:

(a) First, we altered the conditional probabilities of one project. We chose project P_3 owing to its central position in the network. This allowed us to comprehend how misestimating conditional probabilities of one project affects the results for all other projects in the ITPP.
(b) Second, we altered the conditional probabilities of all projects to account for the model's general sensitivity.

We used a range of −50% to +50% concerning the initial estimation provided in Table 2. For instance, if the initial estimation $P(P_i = F|P_j, P_k)$ was 0.40, we computed the RE for all values between 0.20 (i.e. −50% concerning 0.40) and 0.60 (i.e. +50% concerning 0.40) for this probability. Notably, a probability p cannot accept values greater than 1. This implies that, for some entries in our CPTs (for values of $p > \frac{2}{3}$, as $\frac{2}{3} * 150\% = 1$), we must limit the values in our analysis and set them to $p = 1$ to prevent them from exceeding the boundary. In both cases, a and b, we altered the entries of CPTs with the same step size, i.e. we altered the entries for project P_3 (case a) and all entries of the CPT (case b) by +1% in one step.

Fig. 4 provides the RE for all projects within the given range. On the left, we depict case a, and case b on the right. In both cases, an increase in RE values occurs for increased conditional probability values of failure. In case a, in which we address the effect of changing the CPT values of project P_3, we observe that the RE values of most projects do not change

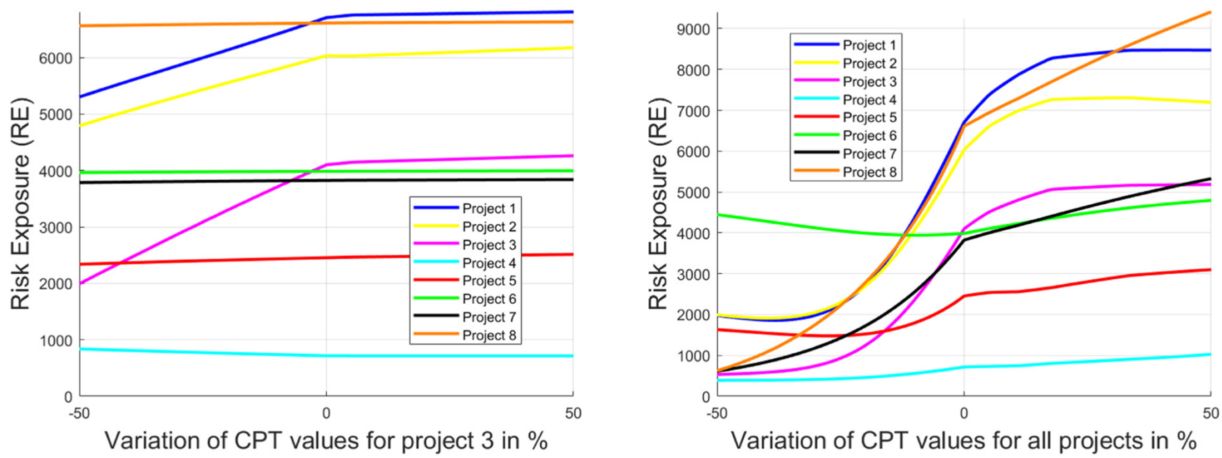

Fig. 4. Risk exposure for all projects for varying CPT values of P_3 (case a) and for varying CPT values of all projects (case b).

much. Particularly for projects P_1, P_2, and P_3, we observed an increase in the RE until our initial setup (0%) is reached. When altering the conditional probabilities of failure for project P_3, in a Bayesian network, this is explained by a more likely failure of preceding projects. Thus, the RE values are comprehensible as project P_3 directly depends on projects P_1 and P_2. The second eye-catching effect is that this increase flattens after having reached the initial setup, owing to the conditional failure probabilities of P_3, which are already close to 1 or even equal (see Table 2); thus, as noted, an increase in these values is only partially possible. Similar effects can be observed for other projects. Overall, our method shows stable behavior.

In case b, in which we address the effects of changing the CPT values of all projects, we observed similar effects. We observed a kink in almost all lines, for the reasons explained above. Also, almost all RE values increased as we expected when increasing the conditional probabilities of failure. We observe that the RE values of projects P_4, P_5, and P_6 showed only slight changes, while all other projects showed a comparatively strong increase in RE. This is a comprehensible result, since the RE of P_6 only consists of the TCF of P_6, because no other projects depend on it. Nonetheless, the RE of project P_6 is particularly interesting, since it barely changed. Thus, for lower estimated conditional failure probabilities, P_6 is by far the most critical project in the ITPP, while it becomes less critical compared to other projects with increased failure probabilities.

Fig. 4 illustrates that altered CPT entries affect the assessment of criticality in an ITPP. As expected, increased CPT entries (i.e. higher probabilities of failure) increase the RE values. In case a, especially the REs of the parents of P_3 and P_3 change, i.e. a misestimation of CPT entries of a particular project affects the RE values of its parents. The other projects' REs varied little. From case b, we can conclude that the ranking of projects in terms of their RE depends on their position in the network and the CPT values. Assuming low probabilites of failure, one project (e.g. P_6) may provide the highest RE in the ITPP, assuming higher probabilites of failure, the RE of this project (e.g. P_6) may barely change, but others become more critical.

5. Discussion

The current project management as well as ITPP management literatures often neglect dependencies' effects, although dependencies can significantly increase the risk of project failure (Buhl, 2012; Centeno et al., 2015; Graves et al., 2003; Martínez and Fernandez-Rodriguez, 2015). Several approaches incorporate dependencies between single projects. In particular, transitive dependencies are seldom addressed in an ITPP context (Beer et al., 2015; Wolf, 2015). Further, very few approaches have sought to integrate different dependency types (Radszuwill and Fridgen, 2017). To address this research gap, our approach has accounted for transitive resource and technical dependencies in ITPPs. We drew on the notion of criticality, which is well known on a project level (Kuchta, 2001) and transferred it to the project portfolio level (Beer et al., 2015; Wolf, 2015).

We investigated how to analyze and assess single projects' criticality in ITPPs. Thus, we followed the network interpretation for ITPPs (Beer et al., 2015; Radszuwill and Fridgen, 2017; Wolf, 2015), which allowed us to incorporate transitive dependency structures and the notion of criticality, both of which are commonly used in network analysis (cf. Keeling and Eames, 2005; cf. Škerlavaj et al., 2010). As is usual for Bayesian network models, we incorporated conditional probabilities of failure for each project. Notably, various interpretations of failure have been discussed in the literature (cf. Atkinson, 1999). Since definitions of failure can be very context-specific or company-specific, we refrained from providing a general definition. However, in practice, failure should be explicitly defined so as to avoid obscurities in data gathering. We also incorporated each project's total cost of failure and then calculated each project's risk exposure in the ITPP. Thus, we provided a new and economically interpretable assessment for single projects' criticality in ITPPs, considering both transitive resource and technical dependencies. We addressed the research gap – that existing approaches for ITPP assessment based on Markowitz (1952) (Beer et al., 2013; Marchewka and Keil, 1995; Wehrmann et al., 2006), linear programming (Ghasemzadeh and Archer, 2000; Lee and Kim, 2001), or real options (Bardhan et al., 2004; Benaroch, 2002; Schwartz and Zozaya-Gorostiza, 2003) neglected the key property of transitive dependencies in ITPPs. Further, to date, Beer et al.'s (2015) approach is the only one that allows one to incorporate different dependency types in an ITPP assessment. Our method provides the opportunity to incorporate both resource and technical dependencies – as the two key dependency types that affect portfolio risk.

In our application example, we set out how the approach can be used in practice. Our approach requires the estimating of CPT values and the cost of failure, which makes data gathering fairly straightforward. However, assuring estimation accuracy can be challenging. While there are several studies on estimation accuracy and best practices can be found in the literature (Jørgensen, 2004), estimating CPTs always bears the risk of misestimation errors. Our sensitivity analysis revealed that an awareness of misestimation is key when using our method. Although small misestimations posed no problems to our method's results, single projects' criticality can change fairly strongly compared to other projects in the same ITPP when CPT estimations change.

Single projects' criticality in terms of RE can differ greatly. Compared to methods that provide a risk measure for the entire ITPP, our method provides distinct insights into which projects are critical and to what extent within an ITPP. In our example, three projects (P_1, P_2, and P_8) had a much higher RE than all other projects. Such effects are particularly important when assessing large ITPPs that should not be overlooked by one person. Imagine an ITPP of 50 or more projects, a size common in large organizations. Owing to risk accumulation effects caused by transitive dependencies, a small number of projects may account for a large percentage of the overall risk. Assessing such a portfolio's criticality, our method allows one to identify these critical projects. In line with this, for resources, holistic resource leveling approaches, as suggested by Neumann and Zimmermann (2000), may be a first step towards risk mitigation.

We outlined that a project's criticality depends on its position in the network. The more (transitive) dependencies a project has to subsequent projects (other things being equal), the more critical it is compared to others, because the failure of an early project may affect subsequent projects. Our Bayesian network approach allows one to analyze and assess the criticality of single projects in ITPPs and facilitates a new perspective for ITPP (risk) management that goes beyond existing approaches which, if at all, usually only account for bilateral dependencies. Our method provides the possibility to identify the projects that are critical in terms of RE, enabling improved ITPP management decisions.

6. Conclusion and avenues for future research

Owing to a multitude of projects and interdependencies, ITPPs are now best described as IT project networks. In such complex and interdependent network-like portfolios, a single project's failure may be crucial to a portfolio's success. Following Meredith et al.'s (1989) research paradigm, we developed a new approach to assess single IT projects' criticality in ITPPs based on Bayesian network modeling, extending the existing body of knowledge in both information systems and project management research. Our method integrates transitive resource and technical dependencies and project-specific influence factors, incorporating a notion of uncertainty. Thus, we have overcome the main drawbacks of prevailing ITPP criticality assessment methods: the missing incorporation of dependencies. In particular, we have incorporated transitive dependencies and different dependency types. Our method assigns risk exposure to each project as a measure of individual projects' criticality. Thus, we provide information on how critical a single project is for an ITPP's success, a question that becomes more important, the more complex ITPPs become; to date, this has barely been addressed in the literature. Existing methods mostly compute an overall portfolio risk. Our method shows that Bayesian network modeling approaches prove useful for criticality analysis in ITPP management. Besides the outlined benefits, our method can be applied fairly straightforward in practice, since only data for CPT values and the cost of failure is necessary.

In our evaluation, we used a real-world application example and conducted a sensitivity analysis as a first step of testing (Meredith et al., 1989). We have pointed out that a small percentage of projects in an ITPP may account for most of the risk. In particular, our method can reveal which projects are more critical than others in the portfolio. For ITPP management, this kind of information is very valuable. Our results suggest that ITPP management should strive for this information and that critical projects should be monitored more closely than others, since a failure's impact can be massive. Thus, from a risk management perspective, in ITPPs, it is crucial to address single projects' criticality and to consider cascading effects owing to transitive dependencies. This aspect is key for portfolio managers and is a valuable contribution to decision-making. Thus, we have contributed to the formalization of the risk management process in ITPP management, which is positively associated with ITTPs' management quality and their success (Keil et al., 2013; Teller, 2013). This enables efficient risk response actions and better resource allocation (Teller and Kock, 2013). Further, our approach allows one to incorporate different dependency types, while existing methods usually only account for one dependency type (Beer et al., 2015). To date, in research and in practice, resource dependencies and technical dependencies are often only regarded separately when planning and monitoring ITPPs. Our integrated method offers advantages, since it is able to account for the interplay between resources and technical dependencies. Thus, relationships may be revealed that other methods cannot account for. The results of our method vary within a reasonable range when assuming misestimating input parameters. In line with this, our analysis reveals that it is important for ITPP managers to be aware of the probabilities of failure levels. Assuming a low failure probability level for all projects, certain projects may be the most critical in the portfolio. In the same portfolio, assuming a high failure probability, the same projects may no longer be the most critical. Thus, depending on the portfolio (i.e. other projects and dependencies), the same project may be significantly more or less critical for a portfolio's success. Since failure probabilities are based on estimations, portfolio managers should consider whether estimations may be prone to systematic and significant underestimation or overestimation.

Our method has limitations. We assume that IT projects are fine-grained subprojects that only deliver one output; therefore, technical dependencies may not cause a cyclical dependency. Accounting for dependencies between these fine-grained subprojects is necessary for criticality assessment, although in large ITPPs, this will be a challenging and time-consuming task. Although the risk identification has significant positive impacts on risk transparency and on an ITPP's success (Teller and Kock, 2013), the tradeoff between the data gathering efforts and risk assessment's potential benefits must be carefully considered in future research. Our approach relies on expert estimations of projects' failure probabilities. We proposed gathering CPTs of each IT project from the various IT project managers, in collaboration with the ITPP manager. While this increases the method's applicability and feasibility by benefitting from the decentral knowledge of all involved IT project managers, it may also yield deviations in estimating the parameter. So far, our approach has only been tested using one real-world example and simulation. While this is a valid mode of testing (Meredith et al., 1989), testing our method in large real-world scenarios should address the data gathering approach. To further evaluate and validate our method, a case study with several real-world ITPPs should provide a comparison with other existing methods from the literature to point out the importance of accounting for different, transitive dependencies even more clearly.

In line with this, we seek to extend our method by several aspects. So far, our model has integrated dependencies and has assessed single projects' criticality in a portfolio context. Our method may also be extended to provide an overall portfolio assessment. We wish to assess benefits of different dependency types towards a holistic ITPP evaluation method. For instance, integrating the benefits of synergetic effects owing to resource-sharing can be a first research step. Second, we wish to extend our method by incorporating methods such as fuzzy reasoning so as to improve the estimation of input parameters and to reduce estimation biases. Also, using real-world data of large ITPPs to further evaluate and validate our model by comparing with real-world observations (Zhang et al., 2013) is subject to further research.

Declaration of interest

None.

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