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RESEARCH ARTICLE

Systemic risk might jeopardize your IT project portfolio: A qualitative evaluation of risk measures

Julia Amend
FIM Research Center,
Wittelsbacherring 10, 95444
Bayreuth, Germany,
Julia.Amend@fim-rc.de

Florian Guggenmos
FIM Research Center,
Wittelsbacherring 10, 95444
Bayreuth, Germany,
Florian.Guggenmos@fim-rc.de

Nils Urbach
Research Lab for Digital Innovation & Transformation (ditlab), Frankfurt University of Applied Sciences,
Hungener Straße 6, 60389 Frankfurt,
Germany,
Nils.Urbach@fb3.fra-uas.de

Gilbert Fridgen
Interdisciplinary Centre for Security, Reliability and Trust, University of Luxembourg, 29, Avenue J.F Kennedy, L-1855 Luxembourg,
Luxembourg, Gilbert.Fridgen@uni.lu

Abstract
IT project portfolios consist of various projects which depend on each other. Including additional IT projects, which are interdependent with existing ones, affects the IT portfolio's systemic risk, which arises from these interdependencies. To handle this risk, organizations must quantitatively analyze the systemic risk of their IT portfolio. However, an overview and evaluation of risk measures for quantitatively analyzing systemic risk in IT portfolios has been missing. In our study, we first conducted a structured literature review to identify risk measures. We then determined evaluation criteria based on mathematical considerations on how risk measures can be modeled and insights from our literature review. Subsequently, we performed a qualitative, criteria-based evaluation to clarify which risk measure fits specific use cases. Finally, we delineated our findings as three recommendations. Our research supports organizations in better analyzing systemic risk in their IT portfolios by selecting the most appropriate risk measure according to their data or use case, contributing to a more successful IT portfolio management.

Keywords
IT portfolio; IT project; systemic risk; risk measure; qualitative evaluation.

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1. Introduction

The Standish Group (2020) asserts that only 35% of all IT projects are successful in terms of budget and time, emphasizing the IT projects' failures and the importance of project management. Furthermore, Flyvbjerg and Budzier (2011) note that around 16% of all IT projects exceed their budgets by 200%, and despite this, the project cost overruns remain unsolvable (Flyvbjerg et al., 2022). The successful management of IT projects is further challenged when they involve emerging technologies, such as blockchain, artificial intelligence, or quantum computing (Häckel et al., 2017; Häckel et al., 2018; Khan et al., 2022; Rotolo et al., 2015), and, for instance, target digital transformation in organizations (Azhari & Raharjo, 2023; Kohnke et al., 2024; Ngereja et al., 2024; Tarannum et al., 2025). Due to the more challenging management of such types of projects, those bear major risks for organizations. Yet, they also incorporate immense opportunities, such as the potential to drive long-term competitiveness (Fridgen & Moser, 2013; Häckel et al., 2017; Irsak & Barilovic, 2023; Omol, 2024; Otay et al., 2023; Tarannum et al., 2025).

Even though it is desirable to make IT projects successful, a single project's success might be insufficient for organizational success since it neglects a strategic and holistic view of risk, considering that projects are embedded in a complex portfolio environment with a vast of interdependencies (Micán et al., 2020). Thus, organizations must be successful in managing their whole IT project portfolio, hereafter referred to as "IT portfolio", to achieve overall organizational success (Archer & Ghasemzadeh, 1999; Bathallath et al., 2016; Karrenbauer & Breitner, 2022; Schulte et al., 2024). Due to the existing interdependencies between the IT projects included in an IT portfolio, one single IT project failure can affect other IT projects. It can even endanger the whole IT portfolio's success since such a failed IT project can lead to domino effects or so-called cascade failures and induce systemic risk (Ellinas, 2019; Ellinas et al., 2015). Hence, organizations must thoroughly know their IT portfolio, the included IT projects, and their interdependencies to make a well-founded decision regarding project selection and optimize value creation (Bathallath et al., 2016; Karrenbauer & Breitner, 2022; Kundisch & Meier, 2011; Martinsuo & Geraldi, 2020; Vieira et al., 2024). Further, they must perform a systemic risk analysis before deciding whether it is beneficial or harmful to include a new IT project.

For such systemic risk analysis, various risk measures exist to calculate different risk scenarios for different IT portfolio constellations (Bai et al., 2023; Beer et al., 2015; Guggenmos et al., 2019). Yet, organizations usually lack in-depth data with appropriate quality on the interdependencies of single IT projects (Cooley et al., 2012; Guggenmos et al., 2019; Hill et al., 2000; Micán et al., 2020), complicating a thorough systemic risk analysis. Further, until now, the literature lacks an overview of suitable risk measures for analyzing systemic risk in IT portfolios. Even though systemic risk has been extensively researched across several domains, including the financial sector (Acemoglu et al., 2015; Curcio et al., 2023; Hautsch et al., 2015; Zhang et al., 2023), critical infrastructure (Buldyrev et al., 2010; Crucitti et al., 2004; Gao et al., 2011; Motter & Lai, 2002), supply chain networks (Ash & Newth, 2007; Verschuur et al., 2022; Zare-Garizy et al., 2018), IT security in smart factories (Bürger et al., 2019; Miehle et al., 2019), and epidemiology (Brockmann & Helbing, 2013; Kermack & McKendrick, 1927; Pastor-Satorras & Vespignani, 2001), according to (Guggenmos et al., 2019) research for IT portfolios is still in its infancy.

Due to this knowledge gap, we propose the following research question:

Which risk measures are suitable for quantitatively analyzing systemic risk in IT portfolios?

To answer our research question, in Section 2, we describe the essential theoretical foundations of IT portfolios. In Section 3, we elucidate our methodological approach for identifying risk measures and evaluation criteria as well as for performing the qualitative evaluation. In Section 4, we shed light on our findings. We then reflect on our evaluation's results, discuss the implications for theory and practice, and delineate the limitations and future research potentials (Section 5). Finally, we conclude our study by summarizing key insights and contributions (Section 6).

2. Background

Risk management is pivotal for successfully implementing IT projects (Baccarini et al., 2004; Didrage, 2013; Pimchangthong & Boonjing, 2017) but is insufficient since it lacks a strategic and holistic view of risk going beyond the single project perspective and considering the interdependencies between projects (Ghasemi et al., 2018; Guan et al., 2017; Micán et al., 2020; Q. Wang et al., 2017). Thus, successfully managing the vast of interdependencies between projects in IT portfolios is critical for success (Bathallath et al., 2016; Drake & Byrd, 2006; Frey & Buxmann, 2012; Mark & Ingmar, 2004; Vieira et al., 2024). However, literature knows various definitions of *risk*, often depending on the application case. One established definition for risk is provided by March and Shapira (March & Shapira, 1987), who define risk as "*reflecting variation in the distribution of possible outcomes, their likelihoods, and their subjective values*". Following this definition, risks are uncertain events that might occur in partially successful or canceled IT projects (Al-Ahmad et al., 2009; Stoica & Brouse, 2013).

With an IT portfolio management view, the question remains open whether and how a single project's risk can affect the risk of other projects depending on it. The various dependencies between projects in an IT portfolio lead to the concept of a *complex network*, often used by researchers to model IT portfolios and consisting of nodes (projects) and edges (different types of dependencies) (Beer et al., 2015; Ellinas, 2019; Micán et al., 2020; Radszuwill & Fridgen, 2017; Q. Wang et al., 2017; Wolf, 2015). Due to the interdependencies in complex networks, a specific risk type is apparent, namely *systemic risk*, a well-known phenomenon in the financial sector (Acharya et al., 2017; Eisenberg & Noe, 2001; Freixas et al., 2000). It is defined as "*the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidenced by comovements (correlation) among most or all the parts*" (Kaufman & Scott, 2003).

Regarding the concept of *dependencies* researchers use various classifications. Some studies focus on a single type of dependency (Lee & Kim, 2001; Santhanam & Kyparisis, 1996; Tillquist et al., 2002; Zuluaga et al., 2007), while others present a framework of different types (Vieira et al., 2024; Wehrmann et al., 2006; Zimmermann, 2008). For instance, according to Wehrmann et al. (2006) and Beer et al. (2015), dependencies in IT projects are classified into *intra-temporal dependencies* (within one-time step) and *inter-temporal dependencies* (between different time steps), whereas other researchers differentiate between *resource dependencies, technical dependencies,* and *benefits (synergies)* (Lee & Kim, 2001; Martinsuo & Geraldi, 2020; Santhanam & Kyparisis, 1996; Tillquist et al., 2002; Zuluaga et al., 2007). We refer to Vieira et al. (2024) for a more detailed review of project dependencies. Regardless of the type of dependency, those are the reasons why a single project failure can also affect another project, which directly depends on its positive outcome. In the case of this first failed project, the failure can also affect other indirect (also called transitive) dependent projects, which in turn can influence other projects and result in a domino effect. These domino effects and the so-called *cascade failures* describe the spread of failures due to the network's interconnectedness as one systemic risk element (Guggenmos et al., 2019).

The risk of such cascade failures must be considered in all four phases (planning, selection, execution, and evaluation) of the IT project portfolio management process through appropriate systemic risk measures. For instance, Archer and Ghasemzadeh (1999) propose considering project interactions through direct dependencies or resource competition within the selection phase in their project portfolio selection framework. Although research into IT portfolio management has been ongoing for many decades, new technologies, such as artificial intelligence, have contributed to major advances being made in recent years (Costantino et al., 2015; Ha & Madanian, 2020; Pappert & Kusanke, 2023; Prifti, 2022). According to Ha and Madanian (2020), fuzzy approach and artificial neural networks are the top trends approaches in project portfolio selection, while other approaches include Bayesian network, ant colony, decision tree, and machine learning.

This study looks closely at existing systemic risk measures and evaluates their suitability to support the IT project portfolio management process.

3. Method

3.1. Identification of risk measures in IT portfolios

We conducted a structured literature review (SLR) in scientific databases to approach our research question and identify relevant systemic risk measures to quantitatively analyze systemic risk in IT portfolios. This represents our main literature stream (stream 1). Additionally, we searched journals in the field of project management (PM) (stream 2) and information systems (IS) (stream 3) to ensure that we captured potentially relevant literature that was not part of the scientific databases. In our SLR, we focused on the term “projects” since this leads to more results and projects are similar regarding their systemic risk characteristics of “IT projects”, allowing for knowledge transfer. We further did not exclude literature that had a single project perspective. The reason is that the interconnectedness is also apparent for tasks in projects, which has already been stated by Bathallath (Bathallath et al., 2016). Thus, knowledge from the single project perspective is transferable to the portfolio perspective.

Figure 1 illustrates the process of our SLR. For the main literature stream (stream 1), we used the following search string (“IT project” OR “project” OR “IT portfolio” AND “systemic risk” OR “cascade failure”), searching in the fields “title”, “abstract”, and “keywords” to identify relevant studies. We performed a query-based literature search in three scientific databases, namely *ScienceDirect*, *Association for Information Systems (AIS) Electronic Library*; and *Institute of Electrical and Electronics Engineers (IEEE Xplore).* For the additional literature streams 2 and 3, we used the same search string applied on “all fields”. To identify the relevant literature for stream 2, we first identified relevant journals in the PM field by utilizing the Scopus database (search term for journal title: “project”, “projects” and “project management”) to ensure that we capture all project-related journals. We identified eleven PM journals (see Fig. 1). For Stream 3, we drew on the Senior Scholars' Basket of Journals postulated by the Association for Information Systems (AIS). Thus, we considered eleven top IS journals (also see Fig. 1).

Stream 1 resulted in 642 studies. We applied our two exclusion criteria (duplicates and missing focus on analyzing projects or portfolios) when screening titles and abstracts. By doing this, we ranked 635 as “not relevant”. The majority of the non-relevant results (approximately 70%) focused on systemic risks in the financial sector (specifically stock portfolios or interbank networks). As a result, we classified seven studies as potentially relevant. After a deeper examination of the full texts, we included four of these as our primary literary sources because they investigate dedicated quantitative risk measures in projects and portfolios. For stream 2, focusing on PM literature, we found 18 studies, of which seven were potentially relevant after applying our two exclusion criteria. After a deeper examination, we included two out of these seven as our primary literary sources, as they also present dedicated risk measures. For Stream 3, which focused on top IS journals, we identified 35 studies from which no study was relevant after applying our exclusion criteria. Subsequently, for Stream 1 and Stream 2, we identified three additional potentially relevant studies using forward and backward searches for citations in the primary sources set, as Webster and Watson (2002) recommended. We checked for duplicates and screened the full texts of these three added studies. As a result, we identified eight risk measures in sum.

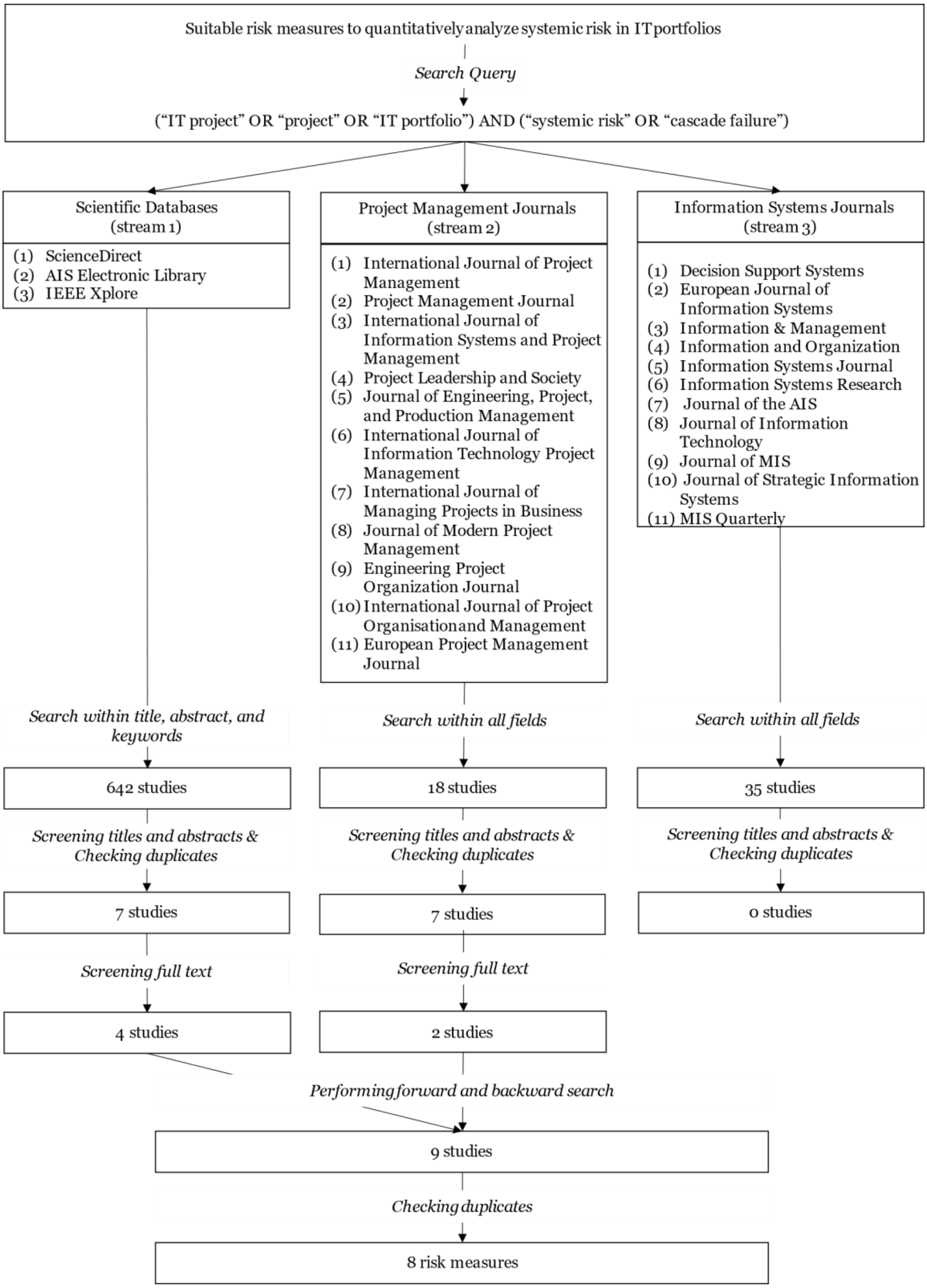


Fig. 1. Process of the structured literature review

3.2. Identification of evaluation criteria for risk measures in IT portfolios

We must first define suitable evaluation criteria to compare the identified systemic risk measures.

To do this, we analyzed how research models systemic risk in IT project portfolios from a mathematical perspective. As already mentioned, researchers mostly model IT project portfolios as complex networks using different sub-types of graph theory like Petri nets, Bayesian networks, or just simple graphs consisting of nodes and edges (Beer et al., 2015; Ellinas, 2019; Micán et al., 2020; Radszuwill & Fridgen, 2017; Q. Wang et al., 2017; Wolf, 2015). Since the systemic risk measures identified in our SLR are also based on graph theory, we focused and limited our evaluation criteria to aspects of systemic risk and their representation in graphs.

We enriched this "abstract" mathematical perspective through screening literature from our SLR regarding evaluation criteria. As a result, we detected Wolf (2015) as a relevant source since he had already derived such a set of evaluation criteria. We further analyzed how the authors of our identified risk measures handled systemic risk. In this step, we took special care to obtain an unbiased result to avoid the generation of a self-fulfilling prophecy.

3.3. Evaluation of risk measures in IT portfolios

We chose a qualitative criteria-based evaluation approach to evaluate the eight identified risk measures, distinguishing between two degrees of fulfillment: "fulfilled" (✓) and "not fulfilled" (✗). Even though we know that reality is more complex than "black or white", we did not include other degrees like "partially fulfilled", as it would be difficult to define a meaningful limit or a specific "partially fulfilled" level and to trace it consistently in our subsequent qualitative assessment of the criteria. In these individual cases, however, we have explicitly explained why we decided on "fulfilled" or "not fulfilled". Appendix A provides insights into the detailed evaluation results, including the justifications for each identified risk measure for why we regard an evaluation criterion as "fulfilled" or "not fulfilled". Further, we refrained from quantitative analysis, as this would require us to calculate all eight risk measures to be examined using a sample portfolio and compare their output. As all risk measures require a large number of different parameters as a database, we could not find real-world data containing all the required parameters. We also decided against generating (random) sample data, as creating the sample data would also strongly bias the evaluation. Therefore, we will stick to a purely qualitative analysis and justify the evaluation of the criteria using, for example, the formulas or parameters on which the risk measures are based.

4. Results

4.1. Risk measures

Based on our SLR, we identified eight risk measures, which we categorized into four categories (Table 1). In terms of systemic risk, Wolf (2015) focused on centrality measures and concluded that the alpha centrality introduced by Bonacich and Lloyd (2001) (RM1) is a suitable risk measure to identify critical projects in IT portfolios. Building on this work, Beer et al. (2015) (RM2) drew on graph theory to assess systemic risks in IT portfolios resulting from direct and indirect dependencies. They combined modern portfolio theory introduced by Markowitz (1952) and alpha centrality to evaluate IT portfolios' overall risks. We summarize these two risk measures in the category "Centrality Measures". Further, we would like to mention Guo et al. (2019) (RM3), who provide an approach based on Motter and Lai (2002) to investigate projects in general. They modeled and analyzed cascading failures in projects for impact evaluation and prediction of cascading failures.

Table 1. An overview of identified risk measures for IT portfolios

Risk measure	Literature Source	Description
Centrality Measures		
RM1: The Alpha Centrality	Bonacich and Lloyd (2001) – backward search	RM1 measures the influence or importance of a node within a network. It supports the identification of key players or influential nodes within a network.
RM2: An Integrated System Risk Quantification Approach	Beer et al. (2015) – scientific databases	RM2 bases on graph theory and targets a rigorous assessment of systemic risk resulting from different types of direct and indirect dependencies within IT portfolios.
Flow Redistribution Models		
RM3: A Load Capacity Model	Guo et al. (2019) – scientific databases	RM3 focuses on investigating cascading failures in projects by first abstracting the project as a weighted directed network with tasks and task interactions and afterward drawing on a cascade model that considers the project's self-protection mechanism.
RM4: A Portfolio Selection Model	Bai et al. (2023) – forward search	RM4 draws on a project portfolio network, in which the initial load and capacity of the projects are considered to simulate the cascading failure process. Finally, it selects the best portfolio option based on the indicator "Strategic Goal Loss Rate" of each project portfolio.
Percolation Models		
RM5: The TD Method	Guggenmos et al. (2019) – scientific databases	RM5 applied the "Susceptible or Infective (SI) model" as a network diffusion model used in epidemiology in the context of IT portfolios to examine systemic risk.
RM6: An Activity Network Approach	Ellinas (2019) – forward search	RM6 draws on an activity network approach usually used for linear cause-and-effect phenomena and is now used to evaluate project systemic risk as nonlinear cause-and-effect phenomena resulting from a cascading failure process.
Other Models		
RM7: A Bayesian Network Approach	Neumeier et al. (2018) – PM journals	RM7 applies Bayesian network modeling to assess the criticality and dependencies of single projects in IT portfolios.
RM8: A Vulnerability Assessment Model	Guo et al. (2020) – PM journals	RM8 uses complex network theory and abstracts the megaproject as a weighted directed network to quantify the vulnerability of megaprojects.

Also following Motter and Lai (2002), Bai et al. (2023) (RM4) proposed a similar approach to investigate the effect of projects' cascading failures in the accomplishment of strategic goals. We summarize both risk measures in the category "Flow Redistribution Models". The next category summarizes "Percolation Models". Guggenmos et al. (2019) (RM5) built on an established epidemiological network diffusion model. They developed the so-called TD method to quantitatively assess systemic risk in IT portfolios. In addition, Ellinas (2019) (RM6) provided a broader perspective on system risk in projects and further supports the assessment of project complexity. Finally, we assigned two risk measures to our last category "Other Models". First, Neumeier et al. (2018) (RM7) applied a Bayesian network for modeling IT portfolios and measuring the criticality of single projects within a portfolio. Second, Guo et al. (2020) (RM8) introduced a risk measure that focuses on megaprojects' vulnerability. Table 1 provides an overview of the identified risk measures and their categories.

4.2. Evaluation criteria

We identified seven suitable criteria to evaluate risk measures by utilizing our mathematical considerations and the work of Wolf (2015) as a starting point. We complemented our findings with the insights from our literature review.

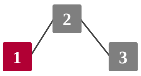
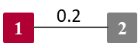
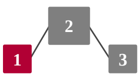
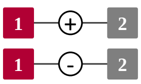
From a mathematical perspective, we conclude that systemic risk measures first must consider dependencies between projects (represented by edges between nodes). Second, these dependencies can be either (un)directed, (un)weighted, or both. Third, to consider network effects, the systemic risk measures must also consider indirect dependencies. These conclusions correspond to Wolf's (2015) findings.

Wolf (2015) presented five criteria, which were the following: The measurements account for direct dependencies (Criterion 1) and indirect dependencies (Criterion 2) between IT projects. Further, the measurement considers the direction (Criterion 3) and the intensity of the dependency (Criterion 4) between IT projects. Finally, in case of an existing dependency, the measurement's result of a specific IT project increases with the criticality of other dependent IT projects (Criterion 5). Based on our literature review insights, we can confirm the suitability of those criteria and must not exclude one. Specifically, our literature review resulted in three main findings: First, previous literature (Beer et al., 2015; Ellinas, 2019; Radszuwill & Fridgen, 2017) indicates inter alia the importance of direct and indirect dependencies by modeling risk in IT portfolios and, therefore, confirms Criterion 1 and 2. Further, regarding Criterion 3, e.g., Ellinas (2019), Guggenmos et al. (2019), and Guo et al. (2019) also build on directed dependencies. Regarding Criterion 4, we can also refer to Ellinas (2019), Guggenmos et al. (2019), and Guo et al. (2019), who consider weighted dependencies within their calculations. For Criterion 5, we mainly build on Bonacich and Lloyd (2001), Beer et al. (2015), Neumeier et al. (2018), and Guo et al. (2020), who confirmed the importance of this characteristic.

Although Wolf's (Wolf, 2015)(2015) evaluation criteria provided a good starting point, we recognized that Wolf's (2015) work misses two essential aspects, resulting in two additional evaluation criteria. First, the literature emphasizes the criticality of an individual IT project as depending not only on the dependency structure but also on project-inherent characteristics (Criterion 6) (Bai et al., 2023; Beer et al., 2013; Neumeier et al., 2018). For example, these studies classify large IT projects as more critical. Further, these studies define the "size" of individual projects based on various parameters, such as already invested or planned budget or employees required. Similarly, emerging IT innovation projects generally have a higher risk of failure (the probability of failure is independent of other projects). Second, Häckel and Hänsch (2014), Radszuwill and Fridgen (2017) and Micán et al. (2020) note that dependencies do not necessarily imply a negative impact. Still, they may also have positive effects, termed "synergies". Although synergies do not primarily affect risks, it is essential to consider both opportunities and risks in an integrated manner because significant synergistic effects can offset the risks caused by dependencies. Thus, a risk measure must simultaneously consider the positive and negative effects, as these may offset each other (Criterion 7).

Table 2 illustrates the study's final set of seven evaluation criteria for risk measures in IT portfolios.

Table 2. Evaluation criteria for risk measures in IT portfolios

ID	Figure	Evaluation Criteria	Primary Source	Description
1		The risk measure considers *direct dependencies* between projects.	Wolf (2015)	Successful accomplishment of individual IT projects is impossible if direct dependencies exist between them.
2		The risk measure for each IT project considers not only direct but also *indirect dependencies*.	Wolf (2015)	Regardless of whether the risk measure examines the individual IT project's criticality or the overall IT portfolio's risk, it must consider indirect dependencies. It is insufficient to consider only the IT projects' direct dependencies.
3		The risk measure considers *directed dependencies* between two IT projects.	Wolf (2015)	A failure in IT project 1 can affect IT project 2 but not vice versa if a directed dependency exists.
4		The risk measure considers the *dependencies' intensity.*	Wolf (2015)	The intensity indicates how strong the IT projects depend on each other. Hereby, both ordinally scaled and cardinally scaled intensities are possible.
5		The risk measure for each IT project considers the *criticality of other dependent IT projects*.	Wolf (2015)	The risk measure must classify an IT project as more critical if other critical IT projects depend on it (cf. recursive calculation) due to its potential for more damage. Additionally, risk measures that focus on the overall risk must consider each IT project's criticality. An offsetting (e.g., addition) of the individual risk measures of all IT projects is insufficient.
6		The risk measure considers at least one *IT project (inherent) parameter*.	Beer et al. (2015), Neumeier et al. (2018), Bai et al. (2023)	IT project's inherent properties contribute to its criticality. In our evaluation, we do not distinguish whether the risk measure considers the project size, its duration, its probability of failure, volatility (variance), other risk parameters (e.g., value at risk), or a flag indicating 'must-have' IT projects, e.g., due to regulatory.
7		The risk measure should provide an integrated view by considering the *positive and negative effects of dependencies*.	Radszuwill and Fridgen (2017)	Generally, risk measures do not account for positive effects. However, positive effects such as synergies can overcompensate negative effects due to dependencies. Thus, it is significant for the risk measure to consider both effects simultaneously.

4.3. Evaluation

Our performed evaluation demonstrated that none of the risk measures fulfilled all seven evaluation criteria. Nevertheless, three risk measures (RM2, RM3, and RM6) fulfilled six of the seven evaluation criteria, only lacking the simultaneous consideration of dependencies' positive and negative effects (Criterion 7). In addition, we observed that besides these, no other analyzed risk measures met Criterion 7.

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Table 3. Summarized evaluation results for the eight risk measures

Risk Measures	1	2	3	4	5	6	7
Centrality Measures							
RM1: The Alpha Centrality	✓	✓	✓	✓	✓	×	×
RM2: An Integrated Systemic Risk Quantification Approach	✓	✓	✓	✓	✓	✓	×
Flow Redistribution Models							
RM3: A Load Capacity Model	✓	✓	✓	✓	✓	✓	×
RM4: A Portfolio Selection Model	✓	✓	×	×	×	✓	×
Percolation Models							
RM5: The TD Method	✓	✓	✓	✓	✓	×	×
RM6: An Activity Network Approach	✓	✓	✓	✓	✓	✓	×
Other Models							
RM7: A Bayesian Network Approach	✓	✓	✓	✓	×	✓	×
RM8: A Vulnerability Assessment Model	✓	✓	✓	✓	×	✓	×

The overarching evaluation results of the eight risk measures are summarized in Table 3.

We provide detailed insights into our qualitative, criteria-based evaluation in the following. Specifically, we present the degree of fulfillment of the risk measures based on each risk measure's formulas or parameters. More details regarding the justifications are part of Appendix A.

4.3.1 Centrality measures

Centrality measures are widely used to analyze networks. Even though a multitude of centrality measures (e.g., degree centrality, closeness centrality, betweenness centrality, or eigenvector centrality) exist, the alpha centrality introduced by Bonacich and Lloyd (2001) remains the most popular measure. In the context of IT portfolios, alpha centrality is the most suitable measure (Wolf, 2015). Thus, we included the "Alpha Centrality" Bonacich and Lloyd (2001) and an "Integrated System Risk Quantification Approach" by Beer et al. (2015), which is based on alpha centrality, in our first category.

RM1: The Alpha Centrality by Bonacich and Lloyd

Alpha centrality, introduced by Bonacich and Lloyd (2001), is based on eigenvector centrality and differs marginally from Katz's (Katz, 1953)(1953) centrality measure. Following Bonacich and Lloyd (2001), the alpha centrality is calculated according to Equation (1).

$$\boldsymbol{x} = (\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1} * \boldsymbol{e} \tag{1}$$

Hereby, the vector $\boldsymbol{x}$ represents the centrality scores for each project. Parameter $\boldsymbol{A}$ indicates the adjacency matrix, which is not limited to symmetric binary entries and reflects the intensity of the IT project dependencies. Matrix $\boldsymbol{I}$ corresponds to the identity matrix and vector $\boldsymbol{e}$ represents an exogenous impact that is independent of the network structure. We adhere to Bonacich and Lloyd (2001) and regard $\boldsymbol{e}$ as a vector of ones such that the alpha centrality weights all nodes equally. The scalar $\alpha \in [0, 1/\lambda_{max})$ represents a ratio for the relative relations between the exogenous and endogenous status of the nodes. The higher the value of alpha, the more significant the influence of matrix $\boldsymbol{A}$. The parameter λ_{max} represents the maximum eigenvalue of $\boldsymbol{A}$. With $\boldsymbol{e} = (1,1, \dots, 1)^T$ for each element x_i of vector $\boldsymbol{x}$ applies $x_i \geq 1$. The alpha centrality examines direct dependencies due to consideration of $\boldsymbol{A}$ (criterion 1: ✓). Further, it also takes into account, indirect dependencies due to the term $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$ (criterion 2: ✓). Since matrix $\boldsymbol{A}$ is not necessarily symmetrical or binary, the alpha centrality regards the direction (criterion 3: ✓) and the intensity of the dependencies (criterion 4: ✓). As the alpha centrality is based on a similar concept idea as the eigenvector centrality, we reformulate equation (1) as $\boldsymbol{x} = \alpha \boldsymbol{A} \boldsymbol{x} + \boldsymbol{e}$. The centrality score $\boldsymbol{x}$ is on both sides of Equation 1 and, thus, this is a recursive calculation. Hence the alpha centrality considers the importance of dependent projects (criterion 5: ✓). Assuming $\boldsymbol{e} = (1,1, \dots, 1)^T$, the alpha centrality does not consider additional project parameters. In case $\boldsymbol{e}$ is replaced with other parameters, each case must be assessed individually to determine its mathematical correctness. For example, using the standard deviation as a risk indicator leads to invalid results (criterion 6: ×). Alpha centrality does not limit the elements of $\boldsymbol{A}$ to a specific interval. Thus, it may imply both positive and negative effects. Generally, the literature indicates negative effects using positive elements ($a_{ij} > 0$). However, the existence of positive and negative a_{ij} simultaneously does not result in the interpretation of the results (vector $\boldsymbol{x}$) in a meaningful way (criterion 7: ×).

RM2: An Integrated Systemic Risk Quantification Approach by Beer et al.

The consideration of variance is a well-established way to analyze portfolio risk. The portfolio theory of Markowitz (1952) in the financial sector represents a well-known approach for analyzing the risk of stock portfolios concerning inter-stock dependencies. Beer et al. (2015) introduced an integrated risk measure (Equation 2) for IT portfolios that combines the concept of portfolio theory (Markowitz, 1952) and a preference function to determine the risk-adjusted IT project value introduced by Beer et al. (2013) to account for overall portfolio risk.

$$\Phi^*(\mu, \sigma) = \sum_i \mu_i - \gamma \sum_i \sigma_i^2 - \gamma \sum_i \sum_{i \neq j} \sigma_i \sigma_j \tilde{\rho}_{ij} \tag{2}$$

In equation (2), μ_i represents the expected value of the IT project, σ_i its corresponding risk (standard deviation), $\tilde{\rho}_{ij}$ the Bravais-Pearson correlation coefficient between each pair of IT projects weighted by a risk aversion parameter γ. Additionally, to include indirect dependencies within the portfolio risk term $\sum_i \sum_{i \neq j} \sigma_i \sigma_j \tilde{\rho}_{ij}$ they adapted alpha centrality as shown in equation (3).

$$\boldsymbol{x} = (\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1} \circ \boldsymbol{E} \tag{3}$$

In the above equation, the mathematical operator '∘' describes an element-wise multiplication of the matrix $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$, containing the transitive dependencies ($a_{ij} \triangleq \tilde{\rho}_{ij}$), and the exogenous matrix $\boldsymbol{E}$, containing the covariances $\sigma_i \sigma_j$. Consequently, the IT portfolio risk term $\sum_i \sum_{i \neq j} \sigma_i \sigma_j \tilde{\rho}_{ij}$ now accounts for transitive dependencies in

IT portfolios. Thus, Beer et al. (Beer et al., 2015) were able to calculate an integrated and adequately risk-adjusted IT portfolio value. For a detailed description of the combining of the alpha centrality and the preference function, we refer to Beer et al. (2015). Analogous to the alpha centrality, due to the consideration of $\boldsymbol{A}$ respectively $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$ the risk measure accounts for direct and indirect dependencies (criterion 1: ✓, criterion 2: ✓). In contrast to the financial sector, the correlation coefficients $\tilde{\rho}_{ij}$ do not have to be symmetrical in IT portfolios and, therefore, indicate the direction of dependencies (criterion 3: ✓). Additionally, the correlation coefficients $\tilde{\rho}_{ij}$ represent the dependencies' intensities (criterion 4: ✓). Due to the use of the alpha centrality, the risk measure also considers the criticality of other projects (criterion 5: ✓). Further, due to the integrated consideration of μ and σ, the risk measure accounts for inherent project parameters (criterion 6: ✓). Finally, the risk measure can only consider positive or negative effects and not both simultaneously (criterion 7: ×).

4.3.2 Flow redistribution models

Flow redistribution models analyze and optimize the flow of resources and information in a system. These focus on identifying bottlenecks by analyzing redistribution flows, aiming for more efficient utilization of resources. Therefore, such models are primarily used in domains such as logistics, traffic planning, and supply chain management but have also been adapted to analyze cascading failures in projects. Thus, next, we summarize a “Load Capacity Model” by Guo et al. (2019) and a “Portfolio Selection Model” by Bai et al. (2023) in this category.

RM3: A Load Capacity Model by Guo et al.

The risk measure provided by Guo et al. (2019) is based on Motter and Lai (2002). Their model initially assigns each project (represented by a node) a specific capacity, indicating the maximum load that it could handle without failure (Crucitti et al., 2004). During the cascading process, the load of each node is recalculated based on centrality measures, such as betweenness centrality (Crucitti et al., 2004), degree centrality (J. Wang, 2013), or out-degree centrality (Tang et al., 2016). If the capacity of a node is lower than its current load, then its predecessor nodes must also handle its load. If one of these is unable to handle the additional load, the cascading process begins. Otherwise, the failed task can restore itself due to the self-protection mechanism. The risk measure is based on the concept introduced by Ellinas et al. (2015) and Ellinas et al. (2016), who modeled the project as a complex network using nodes to represent tasks and edges to describe task interactions. The cascading process results in a set of failed tasks. Guo et al. (2019) applied two established metrics based on Mirzasoleiman et al. (2011) to quantify the impact of a cascading process on a project. However, these metrics are not included in our analysis because these are not a part of the flow redistribution model.

Upon a task's failure, the risk measure by Guo et al. (2019) calculates the additional load to be shared by the predecessor nodes (criterion 1: ✓, criterion 3: ✓) according to their respective weights indicated by the adjacency matrix (criterion 4: ✓). The calculation of the load redistribution is not based on transitive dependencies. However, due to the cascading process indicated by load redistribution, the risk measure also considers indirect predecessors and successors (criterion 2: ✓). Due to the iterative calculation of the cascade process, the risk measure considers the criticality of single projects and all dependent projects (criterion 5: ✓). The risk measure weighs each edge based on the tasks' duration. Moreover, analogous to Ellinas (Ellinas, 2019), the model considers the node weights as dependent on the tasks' duration. Therefore, the risk measure takes at least one task inherent parameter into account (criterion 6: ✓). Finally, based on the cascade model's design, the risk measure can only examine negative effects (criterion 7: ×).

RM4: A Portfolio Selection Model by Bai et al.

Bai et al. (2023) built on their earlier model, Bai et al. (2021), to investigate the effect of projects' cascading failures on the achievement of associated strategic goals. For this purpose, they introduced a new risk measure called "Strategic Goal Loss Rate (SGLR)", indicating the degree S_L, the initial achievement degree (S_0), and the end loss degree (S_l) of the strategic subgoals (equation (4)).

$$S_L = \frac{S_l}{S_0} \tag{4}$$

However, the SGLR was not included in our analysis because it is not part of the cascade model. For a detailed description of SGLR, we refer to Bai et al. (2023). In the cascade model, they consider two types of nodes for complex networks, namely projects and strategic (sub) goals. Analogous to Guo et al. (2019), they base their cascade failure process on a capacity–load model based on Motter and Lai (2002). Bai et al. (2023) use enumeration to identify valid portfolios, meaning those portfolios must meet the organization's strategic (sub)goals. Subsequently, they ran a cascade failure process for each possible portfolio with different failure intensities. Finally, they identified the optimal portfolio using the minimum SGLR. Although Bai et al. (2023) did not design their approach in the context of IT projects, this approach can be applied in this context.

By taking into consideration $d_{j,k}$, which represents the relationships between projects and portfolios, the cascade model of Bai et al. (Bai et al., 2023) accounts for direct dependencies between project j and all other projects k (criterion 1: ✓). Further, since they consider the betweenness centrality in the calculation of the initial risk load of each project, the cascade model also accounts for indirect dependencies (criterion 2: ✓). However, the calculation of direct project interdependencies using $d_{j,k}$ respectively the definition of $d_{j,k} = 1$ indicates that the model does not account for the direction of inter-project dependencies (criterion 3: ×) or their intensity (criterion 4: ×). Analogous to criterion 2, Bai et al. (Bai et al., 2023) additionally account for the criticality of other dependent projects by including the neighbors' weights ω_k, while calculating the initial risk loads (criterion 5: ✓). Moreover, they consider the budget during the calculation of valid portfolios as an additional factor to be taken into account (criterion 6: ✓). Once again, based on the definition of $d_{j,k} = 1$, the cascade model does not account for positive and negative dependencies between two projects j and k (criterion 7: ×).

4.3.3 Percolation models

The third category of percolation models study the phenomenon of percolation in various systems. Percolation occurs when liquids, gases, or other substances flow through a porous medium or network of compounds. These models assist in analyzing and understanding the flow or spread of substances through a medium. Percolation models are used in various fields, such as physics, chemistry, and geology. Additionally, these are relevant in epidemiology to simulate the spread of diseases or in computer science to model the propagation of information or viruses in networks. The cascade effects in portfolios are comparable to the aforementioned application fields of percolation models. Therefore, the "TD Method" by Guggenmos et al. (2019) and an "Activity Network Approach" by Ellinas (2019) have applied these to the field of IT portfolio management.

RM5: The TD Method by Guggenmos et al.

The TD method introduced by Guggenmos et al. (2019) transfers a physical model from epidemiology to IT portfolios modeled as a graph. It is based on the SI (susceptible-infected) cascade model proposed by Kermack and McKendrick (1927), which is a well-known model for simulating the spread of diseases in a society. The TD method distinguishes two states: "on track" (T) and "in difficulty" (D). A project in state T is on track, which implies that it is on time, within scope and within budget. However, it can reach a state of "difficulty" (state D). If a project is in state D, for example, owing to a temporal delay, it can affect other projects that depend on it (e.g., require results of the project in state D). The TD method assumes that projects in state D can affect other projects currently in state T. The TD method does not consider the transition from state D to state T, which implies that a project returns to track. This method calculates a criticality measure (CM) (equation (5)), indicating a project's specific criticality based on a user-specific parameter γ to modify the impact of the speed of propagation.

$$CM_i = 1 + \sum_{t=1}^{n} \frac{\Delta elements_{i,t}^{D}}{t^{\gamma}} \tag{5}$$

The TD method considers direct dependencies indicated by the graph's edges (criterion 1: ✓). Further, the TD method calculates the failure cascade for each timestep t based on the projects in state D in $t-1$ ($\Delta elements_{i,t}^{D}$ in equation (5)). Therefore, it also accounts for indirect dependencies (criterion 2: ✓). Further, the calculation of the cascade process is based on a directed graph (criterion 3: ✓). However, in contrast to Neumeier et al. (2018), the graph does not necessarily have to be acyclic. The original SI cascade model of Kermack and McKendrick (1927) defines the parameter β as constant over time and all edges. It represents the specific infection rate of a disease. However, the TD method reinterprets the infection rate as a non-static parameter. In the TD method, the value of β is based on a dependency's intensity (criterion 4: ✓). Due to the iterative calculation of the cascade process, the criticality measure CM_i does not only consider the criticality of project i, but also of all the dependent projects ($\Delta elements_{i,t}^{D}$ in equation (5)) (criterion 5: ✓). Moreover, the risk measure does not consider any projects' inherent parameters (criterion 6: ×). Finally, due to probabilities, the risk measure can only consider positive or negative effects and not both simultaneously (criterion 7: ×).

RM6: An Activity Network Approach by Ellinas

Ellinas (2019) proposed an analytical model to identify the number of affected tasks, namely nodes, within a project. Through the parameter α the tasks' quality completion can be adjusted in a flexible manner. The model builds upon Ellinas et al. (2015) and Ellinas et al. (2016) and is an advancement of assumptions and data applications of the former models. Their model is based on a specific cascade model and results in two risk measures for each task i. On the one hand, they rank each task's criticality according to its spreading power C_i^{SP} (equation (6)), indicating the task-specific potential to cause cascade effects in later tasks. On the other, they rank all tasks according to their sensitivity C_i^{S} (equation (7)), indicating their susceptibility to failures based on previous tasks.

$$C_i^{SP} = C_i^{SP(topo)} * C_i^{SP(temp)} \tag{6}$$

$$C_i^{S} = C_i^{S(topo)} * C_i^{S(temp)} * C_i^{S(float)} \tag{7}$$

Equations (6) and (7) consider both the topological (topo) effects representing the task's position in the network, the activity-on-the-node network (AON) indicated by a directed graph, and the temporal (temp) effects representing the task's specific duration. The task's sensitivity, further considers the float between two consecutive tasks, representing the viable time to deploy mitigations. Hereby, the AON represents the float by the Euclidean space of the network (length of the edges). For a detailed description of all parameters and the underlying cascade model, we refer to Ellinas et al. (2015) and Ellinas (2019). The calculation of $C_i^{SP(topo)}$ and $C_i^{S(topo)}$ the risk measure considers direct predecessors and successors (criterion 1: ✓). Due to the calculation of cascading effects, the risk measure also considers exclusively indirect predecessors and successors (criterion 2: ✓). Ellinas (2019) uses an adjacency matrix, and due to the directed AON, the risk measure takes into account the direction of dependencies (criterion 3: ✓). The length of the edges regards the time between two tasks and represents the dependency's strength (criterion 4: ✓). Due to the iterative calculation of the cascade process, the risk measure not only considers the criticality of single projects but also of all dependent projects (criterion 5: ✓). Moreover, the risk measure considers at least one task inherent parameter due to the duration of each task (criterion 6: ✓). Finally, due to the design of the cascade model and the calculation of C_i^{SP} and C_i^{S}, the risk measure can only examine negative effects (criterion 7: ×).

4.3.4 Other models

Two models could not be assigned to the above three categories. However, these are relevant risk measures for analyzing cascade failures in complex networks, that is, in IT portfolios. A "Bayesian Network Approach" by Neumeier et al. (2018) and a "Vulnerability Assessment Model" by Guo et al. (2020) are part of this last category.

RM7: A Bayesian Network Approach by Neumeier et al.

Neumeier et al. (2018) introduced a new risk measure for projects to analyze a single IT project's criticality in a portfolio context by applying Bayesian networks. They modeled the portfolio as a directed acyclic graph containing technical dependencies between IT projects and resource dependencies between IT projects and shared resources. Furthermore, the Bayesian network comprises two states: success (T) and failure (F). The risk measure calculates the total cost of failure (TCF) (equation (8)), which describes the extent of economic loss that a specific IT project (here project i) can cause to the IT portfolio, and an integrated cost-risk measure (risk exposure (RE)) (equation (9)).

$$TCF(P_i) = CF(P_i) + \sum_{j \in RP_{i,j}} ECF\left(P_j = F | P_i\right) \tag{8}$$

$$RE = TCF(P_i) * P(P_i = F) \tag{9}$$

They calculated conditional probability tables (CPTs) to build their Bayesian network, which consists of conditional dependencies between directly dependent projects (criterion 1: ✓). During the calculation of the TCF they did not only consider direct dependent projects but all reachable projects (parameter RP in equation (8)) in the IT portfolio (criterion 2: ✓). Lastly, due to the directed graph, the risk measure also takes into consideration directed dependencies (criterion 3: ✓). Furthermore, their risk measure considers a dependency's strength as the conditional dependencies between the projects, containing the edges' intensity (criterion 4: ✓). Further, while calculating the TCF, they sum up costs of failure of project i (parameter $CF(P_i)$ in equation 8) with the expected costs of failure (parameter $ECF\left(P_j = F|P_i\right)$ in equation (8)) of all "attainable projects" indicating indirect dependent projects. Therefore, the risk measure also considers the ECF of other dependent projects but not their criticality as represented by the TCF (criterion 5: ×). Moreover, the risk measure considers the project's inherent probability of failure, as indicated in equation (9) (criterion 6: ✓). Finally, due to probabilities, the risk measure can only consider positive or negative effects (criterion 7: ×).

RM8: A Vulnerability Assessment Model by Guo et al.

A Vulnerability Assessment Model by Guo et al. (2020) is a risk measure that allows the quantitative assessment of project vulnerabilities in megaprojects. They abstracted a megaproject as a weighted directed network and developed a new vulnerability metric. Additionally, they mathematically display communities within a network, representing a stronger relationship between single tasks in projects than loosely connected projects. This community assessment is crucial for the overall vulnerability assessment because it indicates tasks within a project and projects within a megaproject. The risk measure v_z (equation (10)) combines an "outer" vulnerability (v_z^C) that regards interdependencies between a megaproject's projects and an "inner vulnerability" (v_z^D) that considers the internal state of a project to calculate the vulnerability of project z. Further, they defined the maximum vulnerability of all components as the megaproject's vulnerability v_G. For a detailed description of the calculations, we refer to Guo et al. (2020).

$$v_z = \frac{1}{(1 - v_z^D)} * v_z^C \; if \; 0 \leq v_z^D \leq 1 \tag{10}$$

By calculating v_z^C, the risk measure accounts for direct dependencies between project z and all other projects (criterion 1: ✓). Further, by calculating v_z^D, which uses the network efficiency, RM8 also considers indirect dependencies (criterion 2: ✓). The authors modeled the megaproject as a directed network and v_z^C also considers the dependencies' directions (criterion 3: ✓). Analogous to Guo et al. (Guo et al., 2019), the risk measure considers the weights of dependencies on the related projects' duration (criterion 4: ✓). Since the calculation of v_z^C is not recursive, and the risk measure only accounts for direct dependencies, it does not consider other projects' criticality (criterion 5: ×). The risk measure weights each edge based on the tasks' durations, analogous to Guo et al. (2019). Moreover, the risk measure considers the duration of the tasks and projects. Besides, v_z^D indicates a project's efficiency, assuming several tasks may fail (criterion 6: ✓). Due to the calculation of v_z^C, based on weighted edges indicated by an adjacency matrix, the risk measure cannot simultaneously deal with positive and negative effects (criterion 7: ×).

5. Discussion

5.1. Reflection of evaluation results

First, we note that RM1, as part of the category "centrality measures", has been previously stated as a suitable risk measure for IT portfolios by Wolf (2015), which we confirmed with our study since it fits five out of seven criteria. Still, the alpha centrality is inferior to other risk measures. For instance, the alpha centrality did not fulfill Criterion 7 of our evaluation. However, Radszuwill and Fridgen (2017) have investigated how alpha centrality allows for the assessment of synergies, even if not for simultaneous consideration of synergies and risks. Further, we showed that the evaluation criteria Wolf (2015) used do not account for all aspects of systemic risk in IT portfolios, demonstrating that the update and enrichment of the evaluation criteria were reasonable.

Next, through our study, we could detect differences between centrality measures and all other risk measures investigated, further referred to as "simulation-based" risk measures. For instance, centrality measures compute centrality scores, making the computation easy, fast, and straightforward for organizations regarding required input parameters and calculation time. However, the static approach of centrality measures is both a benefit and an impediment simultaneously. In contrast, simulation-based risk measures are more dynamic and provide more flexibility owing to their simulation options. Further, the simulation approach of those measures allows for improved detection and understanding of reciprocal effects, enabling organizations to better represent reality compared to centrality measures. However, to exploit the benefits of simulation-based risk measures, organizations must possess the required input data of an acceptable quality (Micán et al., 2020).

Further, obtaining the input data required for more complex and dynamic risk measures is challenging for organizations. However, attaining this data is sometimes impossible for organizations and requires more effort than organizations are willing to take. Therefore, the first step in analyzing IT portfolios should be elaborating on data availability and quality, which is relevant because the appropriateness and correctness of the presented and evaluated risk measures depend on it. In cases where organizations cannot provide the required information (quality), they should not move forward in analyzing IT portfolios but instead focus on improving their data quality. Otherwise, valid risk management cannot be guaranteed.

Finally, organizations should be aware of the potential risk measures available and their respective strengths and weaknesses. For instance, a risk measure's failure to fulfill specific evaluation criteria compared to others could make the organizations perceive the risk measure as inappropriate, which may not always be the case for every organization. This supposedly poor risk measure can still be a promising risk measure for organizations where the non-fulfilled evaluation criteria are irrelevant or the required input data for those criteria cannot be provided.

5.2. Implications for practice and theory

The overview and evaluation of the risk measures for quantitatively analyzing systemic risk in the IT portfolio enables organizations to apply the most suitable measures according to their available data or use case. Specifically, organizations can use Table 2 and Table 3 as a foundation for their project selection decisions. For these decisions, we want to raise awareness among organizational leaders and provide support for the quantitative analysis of systemic risk in IT portfolios. Thus, we present the following three recommendations:

Recommendation 1: Organizations should know how to quantify their IT portfolio.

All of our identified and evaluated risk measures are quantitative and require respective data for their calculations. Further, all risk measures are based on some kinds of complex networks; thus, for organizations, it is reasonable to know the peculiarities of complex networks and how a real-world IT portfolio can be represented through those. For this quantitative representation and assessment of the IT portfolio, organizations must be capable of providing the obtained data, especially regarding dependencies, for the calculation in sufficient quality. Otherwise, no reliable risk analysis results can be achieved.

Recommendation 2: Organizations should select the most appropriate risk measure according to their available data and use case.

Our overview of the risk measures for analyzing systemic risk in the IT portfolio enables organizations to apply the most suitable measures according to their available data or use case. Specifically, organizations can use Table 2 and Table 3 as a foundation for their decision. On the one hand, they can map their available data with the data required for each risk measure and determine which risk measure is potentially usable according to their database. Second, suppose organizations already know what they want to assess (e.g. single projects' criticality or project selection). In that case, they can determine the suitable risk measure according to their preferred analysis focus and use case.

Recommendation 3: Organizations should be aware that no currently existing risk measure can consider risk and synergies simultaneously, demanding separate risk analyses and a subsequent reflection on the results.

Even though our findings support organizations in applying the most suitable risk measure, organizations are still challenged regarding decisions on integrating emerging IT innovation or digitalization projects in the IT portfolio. One reason for this challenge is that our determined risk measures cannot fulfill the simultaneous consideration of synergies and risks (Criterion 7). Thus, organizations would benefit from performing separate analyses for risks and synergies, as also suggested by Radszuwill and Fridgen (2017). After those separate analyses, organizations must reflect on the results to balance the risk-driven and opportunity-driven perspectives and make their project selection decision. However, in our opinion, this can only be an interim solution approach until risk measures are available to consider risks and synergies simultaneously, as the knowledge gap also stated by Micán et al. (2020) could not be solved until now.

Additionally, this study makes two theoretical contributions. First, we provide an overview of risk measures to quantitatively analyze systemic risk in IT portfolios that has yet been missing in such a form. We thus add novel knowledge to the existing knowledge base. Second, we updated and enriched the evaluation criteria set proposed by Wolf (2015), suggesting an improved set of criteria to evaluate risk measures in the context of IT portfolios. Through this reassessed set of evaluation criteria, we updated the existing knowledge base.

5.3. Limitations and future research potential

Like each research endeavor, this study is subject to certain limitations. The structured literature review identified eight risk measures suitable for analyzing systemic risk in IT portfolios. However, derivatives or other risk measures may also be appropriate for quantifying the systemic risk in IT portfolios, which we have not included yet. Second, for our evaluation criteria, we primarily drew on the set of evaluation criteria by Wolf (2015), which we updated and enriched. However, certain aspects may not have been covered by our evaluation criteria. Nevertheless, to the best of our knowledge, these criteria cover the main aspects of systemic risk.

Overall, we acknowledge that the current body of literature provides a sufficient understanding of promising risk measures for assessing the criticality of individual IT projects or the entire IT portfolio. Nevertheless, further research is warranted in this field. First, even though previous researchers have already demanded means to analyze risks and synergies in an integrated manner (Micán et al., 2020), this knowledge gap still exists. Second, to support future research in developing suitable risk measures, researchers should utilize our set of evaluation criteria as input for requirements. Third, collecting the necessary data of adequate quality from IT projects and IT portfolios takes time and effort for organizations. Thus, developing risk measures to illustrate reality as well as possible may unnecessarily maximize complexity and is unreasonable. Instead, it is more desirable to drive research for risk measures that are more pragmatic to achieve a better cost-benefit ratio for organizations. Lastly, future research should focus on assessing how digital technologies (such as AI and machine learning) can support the process of data collection required for calculating the risk measures or how those technologies can contribute to more pragmatism, including an easier calculation of various IT portfolio scenarios and management-optimized display of results.

6. Conclusion

Considering the high percentage of project failures (The Standish Group, 2018, 2020) and the fact that these are partly attributed to the interdependencies of the projects (Beer et al., 2015; Ellinas et al., 2015; Guggenmos et al., 2019), it underscores the need to quantitatively analyze systemic risk in IT portfolios to support the successful management of the IT portfolio. However, an overview of suitable risk measures for analyzing systemic risk in IT portfolios has yet to be provided.

We filled this knowledge gap and performed a SLR to identify risk measures that enabled us to determine the most critical IT projects in an IT portfolio and the overall IT portfolio risk considering systemic risk. To evaluate the eight identified risk measures, we used a set of seven evaluation criteria derived from mathematical considerations on how risk measures can be modeled and complemented with insights from the SLR. Our qualitative, criteria-based evaluation revealed that none of the identified risk measures fulfilled all evaluation criteria, and no risk measure fulfilled Criterion 7, focusing on the simultaneous consideration of risks and synergies.

Our study provides the yet missing overview of risk measures suitable for quantitatively analyzing systemic risk in IT portfolios. We further provided an updated set of evaluation criteria that shall function as input for the future development of risk measures. Moreover, our research findings support organizations in determining the most suitable risk measure regarding their available data and use case, contributing to more successful IT portfolio management and, ultimately, to overall organizational success.

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Appendix A. Detailed evaluation results

Table A1. Detailed evaluation results for RM1

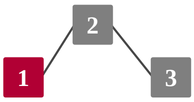
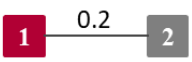
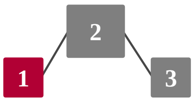
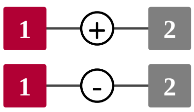
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	The adjacency matrix $\boldsymbol{A}$ represents the graph. Thereby each element $a_{i,j} \neq 0$ represents an existing direct dependency between i and j. By considering $\boldsymbol{A}$, the Alpha centrality considers direct dependencies.
2	 indirect dependencies	✓	While the adjacency matrix $\boldsymbol{A}$ only contains direct dependencies, the term $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$ results in a matrix containing direct and indirect dependencies. Therefore, the Alpha centrality also considers indirect dependencies.
3	 directed dependencies	✓	While the elements $a_{i,j} \neq 0$ represent existing direct dependencies between i and j the adjacency matrix does not need to be a symmetric matrix ($a_{i,j} = a_{j,i}$). In case of an unsemmetric adjacency matrix $\boldsymbol{A}$, the alpha centrality considers the direction of dependencies.
4	 dependencies' intensity	✓	While the elements $a_{i,j} \neq 0$ represent existing direct dependencies between i and j the adjacency matrix do not need to be binary ($a_{i,j} \in \{0,1\}$) but can take any value ($a_{i,j} \in \mathbb{R}$). Therefore, the alpha centrality considers the weight of dependencies.
5	 criticality of other dependent IT projects	✓	The alpha centrality can be transformed as follows: $\boldsymbol{x} = (\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1} * \boldsymbol{e} \Leftrightarrow \boldsymbol{x} = \alpha \boldsymbol{A} \boldsymbol{x} + \boldsymbol{e}$ Now, the centrality score $\boldsymbol{x}$ is on both sides. Thus, this is a recursive calculation. This means that each centrality score depends on all other centrality scores. Therefore, the alpha centrality considers the centrality (importance) of dependent elements (projects).
6	 IT project (inherent) parameter	×	According to Bonacich and Lloyd (2001), the vector $\boldsymbol{e}$ can reflect the effects of different external status characteristics (e.g. popularity). Therefore, this criterion should be fulfilled. However, the result is not always correct in a mathematical sense. For example, if the vector $\boldsymbol{e}$ contains the standard deviation σ_i as a project-specific risk measure, the calculation leads to "incorrect" results, as the rules for calculating a variance or covariance are disregarded. As the standard deviation is a common measure of risk in project portfolio management, we regard this criterion as not fulfilled.
7	 positive and negative effects of dependencies	×	Since the elements $a_{i,j}$ of $\boldsymbol{A}$ or not limited ($a_{i,j} \in \mathbb{R}$) they can also be positive or negative. Therefore, the alpha centrality might consider dependencies and synergies. However, the calculation of $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$ while $\boldsymbol{A}$ contains positive and negative elements $a_{i,j}$ at the same time leads to results that can not be interpretated in a meaningful way. Besides that, each element $a_{i,j}$ can only be positive or negative. Therefore, the alpha centrality can not consider dependencies and synergies simultaneously.

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Table A2. Detailed evaluation results for RM2

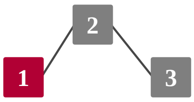
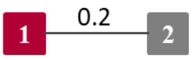
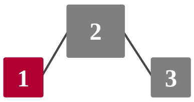
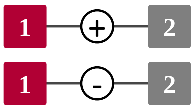
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	Since the portfolio risk term $\sum_i \sum_{i \neq j} \sigma_i \sigma_j \tilde{\rho}_{ij}$ of RM2 base on the alpha centrality the same reasoning applies for the most part. The adjacency matrix $\boldsymbol{A}$ represents the graph. Thereby each element $a_{i,j} \neq 0$ represents an existing direct dependency between i and j. Through the consideration of $\boldsymbol{A}$ RM2 considers direct dependencies.
2	 indirect dependencies	✓	While the adjacency matrix $\boldsymbol{A}$ only contains direct dependencies, the term $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$ results in a matrix containing direct and indirect dependencies. Therefore, the RM2 also considers indirect dependencies.
3	 directed dependencies	✓	While the elements $a_{i,j} \neq 0$ represent existing direct dependencies between i and j the adjacency matrix does not need to be a symmetric matrix ($a_{i,j} = a_{j,i}$). In case of an asymmetric adjacency matrix $\boldsymbol{A}$**,** RM2 considers the direction of dependencies.
4	 dependencies' intensity	✓	While the elements $a_{i,j} \neq 0$ represent existing direct dependencies between i and j the adjacency matrix does not need to be binary ($a_{i,j} \in \{0,1\}$) but can take any value ($a_{i,j} \in \mathbb{R}$). Therefore, RM2 considers the weight of dependencies.
5	 criticality of other dependent IT projects	✓	The term of the alpha centrality can be transformed as follows: $$\boldsymbol{x} = (\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1} * \boldsymbol{e} \;\Leftrightarrow\; \boldsymbol{x} = \alpha \boldsymbol{A} \boldsymbol{x} + \boldsymbol{e}$$ Now, the centrality score $\boldsymbol{x}$ is on both sides. Thus, this is a recursive calculation. This means that each centrality score depends on all other centrality scores. Therefore, RM2 considers the centrality (importance) of dependent elements (projects).
6	 IT project (inherent) parameter	✓	The portfolio risk term $\sum_i \sum_{i \neq j} \sigma_i \sigma_j \tilde{\rho}_{ij}$ is an adaption of the alpha centrality. $$\boldsymbol{x} = (\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1} \circ \boldsymbol{E}$$ In the equation, the mathematical operator '∘' describes an element-wise multiplication of the matrix $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$, containing the transitive dependencies ($a_{ij} \triangleq \tilde{\rho}_{ij}$), and the exogenous matrix $\boldsymbol{E}$, containing the covariances $\sigma_i \sigma_j$ as a project risk measure. Consequently, the IT portfolio risk term $\sum_i \sum_{i \neq j} \sigma_i \sigma_j \tilde{\rho}_{ij}$ now accounts for a project inherent parameter. Further, besides risk (σ), RM2 also considers a second project inherent paramater, namely the expected value (μ). Therefore we regard criterion 6 as fulfilled.
7	 positive and negative effects of dependencies	×	Since RM2 only considers dependencies in its IT portfolio risk term, for criterion 7, the same reasoning applies to alpha centrality. Since the elements $a_{i,j}$ of $\boldsymbol{A}$ are not limited ($a_{i,j} \in \mathbb{R}$) they can also be positive or negative. Therefore, the alpha centrality might consider dependencies and synergies. However, the calculation of $(\boldsymbol{I} - \alpha * \boldsymbol{A})^{-1}$ while $\boldsymbol{A}$ contains positive and negative elements $a_{i,j}$ at the same time leads to results that can not be interpretated in a meaningful way. Besides that each element $a_{i,j}$ can only be positive or negative. Therefore, RM 2 cannot consider dependencies and synergies simultaneously.

Table A3 Detailed evaluation results for RM3

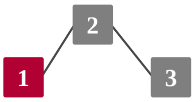
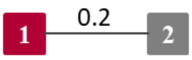
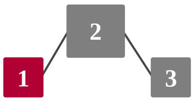
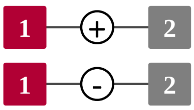
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	Guo et al. (2019) model dependencies between directly consecutive tasks to build a suitable project network. Their cascade model considers direct dependencies by considering the parameters $w_{i,j}$ representing the elements of the graph's adjacency matrix. Therefore, we regard this criterion as fulfilled.
2	 indirect dependencies	✓	Unlike other risk measures, like alpha centrality, RM3 does not explicitly consider the indirect dependencies. However, during the cascade process, the loads are continuously redistributed according to the following rule: $$\begin{cases} \Delta L_{k,p} = L_k(0)\frac{w_{k,p}}{\sum'_{b\in\Gamma'_k} w_{k,b'}} \\ \Delta L_{k,q} = L_k(0)\frac{w_{k,q}}{\sum'_{b\in\Gamma'_k} w_{k,b'}} \end{cases}$$ Thereby, the parameter $\Gamma_k{}'$ represents the set of successor neighbor nodes directly connecting from node k. Through the continuous consideration of all successor nodes during the cascade process, RM3 also considers indirect dependencies and therefore, we regard criterion 2 as fulfilled.
3	 directed dependencies	✓	Also, for RM3, the adjacency matrix does not need to be symmetric. Rather, this approach explicitly relies on asymmetric adjacency matrices since only the subsequent nodes are considered. Therefore, RM3 also considers directed dependencies.
4	 dependencies' intensity	✓	RM3 is based on the idea that tasks that take longer tend to have a greater impact than shorter tasks. Therefore, the authors assume that the node weight ($w_{i,j}$) is relevant to the task duration since edges between the nodes with higher weights tend to have a more significant influence than edges between the nodes with smaller weights (Guo et al., 2019). Therefore, RM3 considers the intensity of dependencies.
5	 criticality of other dependent IT projects	✓	For criterion 5, the same reasoning applies as for criterion 2. Since the cascade process redistributes the loads of all nodes and calculates whether a node fails (node load exceeds its capacity), a node's failure will lead to another load redistribution. Due to this, we conclude that RM3 also considers the criticality of dependent tasks (in this case: successor neighbor tasks) and, therefore, regard criterion 5 as fulfilled.
6	 IT project (inherent) parameter	✓	As mentioned for criterion 4, RM3 calculates the weights of all dependencies based on the tasks' durations, representing a project inherent parameter. Therefore, RM3 fulfills criterion 6.
7	 positive and negative effects of dependencies	×	First, the way how Guo et al. (2019) model their graph (based on the the elements of the adjacency matrics $w_{i,j}$) does not consider synergies. Second, the design of their cascade model only considers the negative effects of dependencies and offers no possibility to consider synergies. Therefore, RM3 does not fulfill criterion 7.

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Table A4. Detailed evaluation results for RM4

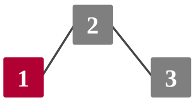
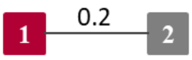
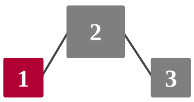
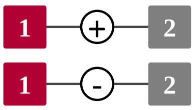
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	Bai et al. (2023) focus on the selection of an optimal project portfolio indicated by the smallest “Strategic Goal Loss Rate” (SGLR). To do this, they model their project portfolio using two different types of nodes and two sets of edges. On the one hand, strategic subgoals are independent of each other, and on the other hand, the projects themselves depend on each other. Further, the strategic subgoals also depend on specific projects. Dependencies between projects exist if and only if they jointly achieve the same strategic subgoal. Therefore, we regard criterion 1 as fulfilled.
2	 indirect dependencies	✓	RM4 also base on load redistribution. The authors calculate the initial load of each project j as follows: $$L_j = (1+\alpha)\left(B_j w_j \sum\nolimits_{k \in M_j} w_k\right)^{\beta}$$ In this formula B_j represents the betweenes (centrality) of project j, which bases on the number of shortest paths between all other nodes through node j. Therefore, RM4 implicitly considers indirect dependencies, and we regard criterion 2 as fulfilled.
3	 directed dependencies	×	For criterion 3, we only consider the dependencies between different projects ($d_{j,k}$) and neglect those between projects and strategic sub-goals. The authors define dependencies between projects binary. $$d_{j,k} = \begin{cases} 1, & \text{if project } j \text{ and project } k \text{ can achieve the same subgoal} \\ 0, & \text{otherwise} \end{cases}$$ This results in a symmetric adjacency matrix, and therefore, RM4 does not consider directed dependencies. So, we regard criterion 3 as not fulfilled.
4	 dependencies’ intensity	×	As mentioned for criterion 3, the authors defined the dependencies between projects as binary. This implies that RM4 does not consider individual intensities of dependencies. Therefore, RM4 does not fulfill criterion 4.
5	 criticality of other dependent IT projects	✓	Since the calculation of a project’s (initial and during load redistribution) load depends on dependent projects (implicitly considered by the parameter w_j) RM4 also considers the criticality of other dependent projects. Further, RM4 bases on the same idea as RM3. Consequently, the same reasoning regarding the cascade failure process applies to RM4. Therefore, RM4 fulfills criterion 5.
6	 IT project (inherent) parameter	✓	Before comparing all possible project portfolios regarding the SGLR, the authors reduced the set of potentially relevant project portfolios by applying two rules: 1) All strategic subgoals are achieved. 2) The total budget of the project portfolio does not exceed the enterprise’s budget limitation. To calculate the budget limit, the authors assigned each project a specific budget necessary to carry out the project. By doing so, RM4 considers the budget as a project inherent parameter. Therefore, we regard criterion 6 as fulfilled.
7	 positive and negative effects of dependencies	×	For criterion 7, the same reasoning applies to RM4, as to RM3. The adjacency matrix cannot handle positive and negative effects. Besides, analogous to RM3, RM4 was designed to consider dependencies, not synergies. Therefore, we regard criterion 7 as not fulfilled.

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Table A5. Detailed evaluation results for RM5

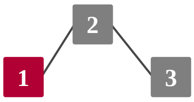
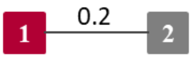
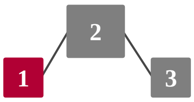
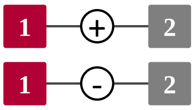
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	The TD method, introduced by Guggenmos et al. (2019), is a simulation-based approach. One required input parameter is a graph (complex network) representing the IT project portfolio. This graph considers projects (nodes) and their direct dependencies (edges). Consequently, RM5 fulfills criterion 1.
2	 indirect dependencies	✓	Like the load redistribution models, the TD method does not explicitly consider indirect dependencies. However, through the simulation process, RM5 accounts for these indirect dependencies. In each (time) step of the simulation, the algorithm simulates whether a failure spreads from "infected" nodes to some of its neighbor nodes. By doing this, the process considers indirect dependencies, and we regard criterion 2 as fulfilled.
3	 directed dependencies	✓	According to the authors, the graph, which the TD method uses as an input parameter, is a directed graph. This means that the associated adjacency matrix is not symmetric or does not have to be symmetric. Therefore, RM5 fulfills criterion 3.
4	 dependencies' intensity	✓	Further, the authors decided to use a non-binary adjacency matrix. While in the original SI cascade model, introduced by Kermack and McKendrick (1927), the "infection rate" is constant over time and for all persons, in the TD method, this parameter is only constant over time but individual for each dependency. In the TD method, the dependencies intensities are limited to the interval $[0; 1]$ and represent the probability that a failure spreads to the successor node. Thus, we regard criterion 4 as fulfilled.
5	 criticality of other dependent IT projects	✓	For criterion 5, the same reasoning applies like to criterion 2 and the load redistribution models. The TD method implicitly considers the criticality of other dependent IT projects by the design of the simulation process. This can especially be seen in the calculation of the criticality measure CM_i. $$CM_i = 1 + \sum_{t=1}^{n} \frac{\Delta elements_{i,t}^{D}}{t^{\gamma}}$$ CM_i does not only consider the criticality of project i, but also of all the dependent projects ($\Delta elements_{i,t}^{D}$). Therefore, RM5 fulfills criterion 5.
6	 IT project (inherent) parameter	×	The TD method bases on three input parameters. First, the graph, representing the IT project portfolio. Second, a set of initially failed projects and, third, the number of time steps that should be simulated. Further, the required graph only consists of projects (nodes) and their directed and weighted dependencies (edges). No additional project inherent parameters are used during the simulation, leading to the statement that RM5 does not consider criterion 6.
7	 positive and negative effects of dependencies	×	As mentioned for criterion 4, the authors interpreted the dependencies' weights as a probability for the failures' spread. Since probabilities can only be positive, the TD method cannot consider negative and positive effects at the same time. Although the authors used the TD method only for dependencies, in our opinion, it can also be used with synergies but not at the same time. Therefore, we consider criterion 7 as not fulfilled.

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Table A6. Detailed evaluation results for RM6

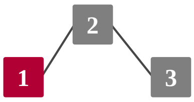
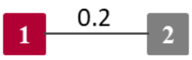
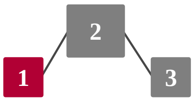
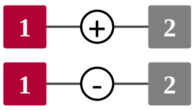
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	The Activity Network Approach, introduced by Ellinas (2019), uses an activity-on-the-node (AON) network notation in the form of a directed graph. In this AON every node i, corresponds to task i and a directed link $e_{i,j}$ accounts for the precedence relationship between tasks i and j. A dependency between task i and j requires that task i must first be completed for task j to start. Therefore, task j is, in relation to task i, a downstream task (similarly, task i is, in relation to task j, an upstream task). As a result, a temporal direction to all possible failures exists, where a failure in task i can only affect downstream tasks but not upstream tasks, as these tasks have already been completed. Therefore, RM6 considers direct dependencies and criterion 1 is fulfilled.
2	 indirect dependencies	✓	For RM6, the authors inter alia use the parameter $C_i^{SP(topo)}$ to calculate the spreading power C_i^{SP} of each node i. $C_i^{SP(topo)}$ considers the position of a task within the AON network by accounting for the effectiveness by which task i can reach, and hence affect its immediate downstream tasks(s) over all possible paths. In addition, longer paths contribute less to the overall spreading power as they are less likely to be traversed compared to shorter, more direct paths. Since this parameter also accounts for indirect dependencies, we regard criterion 2 as fulfilled.
3	 directed dependencies	✓	As already mentioned for criterion 1, RM6 bases on an AON represented by a directed graph. Further, $C_i^{SP(topo)}$ also considers downstream tasks. Therefore, RM6 considers directed dependencies, and we regard criterion 3 as fulfilled.
4	 dependencies' intensity	✓	Besides the network structure $C_i^{SP(topo)}$, the spreading power also considers temporal aspecs $C_i^{SP(temp)}$. The parameter $C_i^{SP(temp)}$ is calculated as the ratio between the duration of task i and the project duration (sum of all task durations). Ellinas (2019) assume that that the longer a task is, the greater its ability to affect its immediate downstream tasks. We conclude that by calculating the spreading power C_i^{SP} RM6 also considers the intensity of dependencies and regard criterion 4 as fulfilled.
5	 criticality of other dependent IT projects	✓	For criterion 5, the same reasoning applies to the TD method (RM5), as to the load redistribution models (RM3 and RM4). RM5 does not explicitly consider the criticality of other dependent projects. However, it considers these implicitly through the design of the cascade process. For instance, the authors calculated new thresholds $\theta_j(new)$ for all downstream tasks j of node i to determine whether some downstream tasks will also fail. Therefore, we conclude that RM6 fulfills criterion 5.
6	 IT project (inherent) parameter	✓	Through the calculation of the spreading power C_i^{SP} respectively its temporal element $C_i^{SP(temp)}$, RM6 accounts for the task duration and, therefore, considers at least one project inherent paramater. So we conclude that RM6 fulfills criterion 6.
7	 positive and negative effects of dependencies	×	Due to the design of the cascade model and the calculation of C_i^{SP} and C_i^{S}, the risk measure can only examine negative effects of dependencies. Analogous to RM5, the authors of RM6 only use their cascade model for dependencies. However, it can also be used with synergies but not simultaneously. Therefore, we consider criterion 7 as not fulfilled.

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Table A7. Detailed evaluation results for RM7

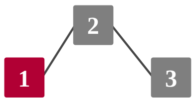
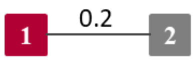
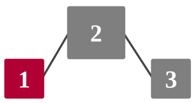
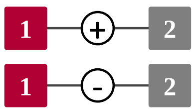
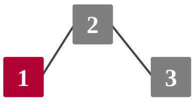
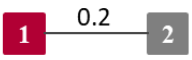
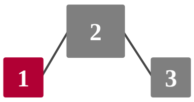
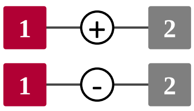
	Criterion	Evaluation	Justification
1	 direct dependencies	✓	RM7, introduced by Neumeier et al. (2018), bases on Bayesian networks. A Bayesian network is a directed acyclic graph (DAG) with nodes and edges. Thereby, edges represent conditional dependencies between nodes. The authors use nodes to model IT projects and shared resources and edges to model dependencies between two IT projects as well as an IT project and a shared resource. Therefore, RM7 considers direct dependencies and criterion 1 is fulfilled.
2	 indirect dependencies	✓	Like the flow redistribution models, RM7 does not explicitly consider indirect dependencies. RM7 considers these implicitly by calculating the total cost of failure (TCF). $$TCF(P_i) = CF(P_i) + \sum_{j \in RP_{i,j}} ECF\left(P_j = F\|P_i\right)$$ In this equation, RM7 sums up the expected cost of failure (ECF) of all reachable projects (RP) j of project i. So, we conclude that RM7 considers indirect dependencies and fulfills criterion 2.
3	 directed dependencies	✓	As mentioned for criterion 1, RM7 bases on a directed acyclic graph (DAG). According to the authors, a node X with direct edge to Y is called a parent of Y, and Y is called its child. Therefore, RM7 considers directed dependencies and fulfills criterion 3.
4	 dependencies' intensity	✓	The authors used conditional probability tables (CPT) to build their Bayesian network. These CPTs contain the strength of edges (conditional dependencies) between directly connected nodes. Therefore, RM7 considers dependencies' intensities and fulfills criterion 4.
5	 criticality of other dependent IT projects	×	While calculating the TCF for project $TCF(P_i)$, RM7 sums up costs of failure of project i ($CF(P_i)$) with the expected costs of failure ($ECF\left(P_j = F\|P_i\right)$) of all reachable projects indicating indirect dependent projects (see criterion 2). Therefore, the risk measure also considers the ECF of other dependent projects. However, since ECF is not the criticality measure (represented by TCF), we conclude that RM7 does not consider the criticality of other dependent IT projects and does not fulfill criterion 5.
6	 IT project (inherent) parameter	✓	Since the Bayesian network builds on conditional dependencies based on the project's inherent failure probabilities, we conclude that RM7 considers one project's inherent parameter. Therefore, RM7 fulfills criterion 6.
7	 positive and negative effects of dependencies	×	For criterion 7, the same reasoning applies as for RM5. Since the dependencies' intensities represent probabilities, RM7 cannot consider positive and negative effects at the same time. Thus, RM7 does not fulfill criterion 7.

Table A8. Detailed evaluation results for RM8

	Criterion	Evaluation	Justification
1	 direct dependencies	✓	RM8, introduced by Guo et al. (2020), builds on a complex network representing a megaproject with many interlinked projects. The authors modeled this network as a directed, weighted graph. In this graph, nodes represent sub-project tasks and edges represent the relationships and the sequential order between these tasks. RM8 considers these dependencies when calculating the “outer” vulnerability (v_z^C). Therefore, we regard criterion 1 as fulfilled.
2	 indirect dependencies	✓	Besides the “outer” vulnerability (v_z^C), RM8 also considers the “inner” vulnerability (v_z^D). The calculation of v_z^D measures the biggest percentage drop in network efficiency. According to the authors, network efficiency reflects the global connectivity of the individual project(s). The calculation of network efficiency is based on the sum of the geodesic distance between all pairs of nodes (here: tasks) in the network. Since the network efficiency considers indirect dependencies, we conclude that RM8 also considers indirect dependencies. Thus, we regard criterion 2 as fulfilled.
3	 directed dependencies	✓	As already mentioned for criterion 1, RM8 builds on a directed graph. RM8 considers these dependencies when calculating the “outer” vulnerability (v_z^C). Therefore, we regard criterion 3 as fulfilled.
4	 dependencies’ intensity	✓	The authors assumed that tasks that take longer tend to have a greater impact than shorter tasks. Therefore, they define the node weight (w_i) as related to the task duration (t_i). Further the node weights should also be represented by the edge weights. Therefore, RM8 uses a weighted adjacency matrix *W*, where $W = [w_{i,j}]$ is an asymmetric $N \times N$ where $w_i = t_i$and $w_j = t_j$. $$w_{i,j} = \begin{cases} (w_i + w_j)/2 & \text{if } n_i \text{ directly connects to } n_j \\ 0 & \text{otherwise} \end{cases}$$ This adjacency matrix is, for instance, used to calculate the “outer” vulnerability (v_z^C). Therefore, we conclude that RM8 considers the dependencies’ intensity and regard criterion 4 as fulfilled.
5	 criticality of other dependent IT projects	×	RM8 considers network effects (see v_z^C) as well as network efficiency (see v_z^D). However, calculating the vulnerability v_z does not consider the criticality of other dependent projects (no recursive calculation). $$v_z = \frac{1}{(1 - v_z^D)} * v_z^C \; if \; 0 \le v_z^D \le 1$$ Therefore, we conclude that RM8 does not fulfill criterion 5.
6	 IT project (inherent) parameter	✓	RM8 builds on the tasks’ durations to calculate the dependencies' intensities. Further, the “inner” vulnerability (v_z^D) indicates a project’s efficiency, assuming several tasks may fail. Therefore, we conclude that RM8 considers project inherent parameters and fulfills criterion 6.
7	 positive and negative effects of dependencies	×	For criterion 7, the same reasoning applies to other RMs, which are based on weighted adjacency matrices, like RM1. Since the calculation of v_z^C is based on weighted edges indicated by an adjacency matrix, we conclude that RM8 cannot simultaneously deal with positive and negative effects. Therefore, RM8 does not fulfill criterion 7.

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Biographical notes

Julia Amend (julia.amend@fim-rc.de) is a business developer for a German insurance company. In her daily work, she enables digital, data-driven business models and drives data analytics activities as the foundation for more needs-oriented customer interactions using AI-based approaches. In her research at FIM Research Center, she explores how organizations can successfully manage digital innovation – considering the IT project perspective and the IT portfolio perspective.

Florian Guggenmos (florian.guggenmos@fim-rc.de) is a project and portfolio manager for a large German industrial concern. In his daily work, he leads and coordinates various projects and initiatives to digitize the organization and its products. In his research at FIM Research Center, he focuses on IT project and portfolio management and disruptive technologies.

Nils Urbach (nils.urbach@fim-rc.de) is Professor of Information Systems and Digital Business as well as Director of the Research Lab for Digital Innovation & Transformation (ditlab) at the Frankfurt University of Applied Sciences. Furthermore, he is Director at the FIM Research Center for Information Management and the Branch Business & Information Systems Engineering of Fraunhofer FIT. In his research, he focuses on the strategic management of digital innovations and the design of organizations in the course of digital transformation. Emerging information technologies and information systems are of particular interest to him regarding their impact on companies and markets.

Gilbert Fridgen (gilbert.fridgen@uni.lu) is Full Professor and PayPal-FNR PEARL Chair in Digital Financial Services at the Interdisciplinary Centre for Security, Reliability, and Trust (SnT), University of Luxembourg and Coordinator of the National Centre of Excellence in Research on Financial Technologies. His research focus is on the transformative effects of digital technologies on individual organizations and the relationship between organizations. A particular technology focus is on emerging technologies like Distributed Ledgers, Digital Identities, Machine Learning, and the Internet-of-Things.