The Benefits of Applying Social Network Analysis to Identify Collaborative Risks

Marco Nunes[1](✉) and António Abreu[2,3](✉)

[1] Department of Industrial Engineering, University of Beira Interior, 6201-001 Covilhã, Portugal
marco.nunes@ubi.pt

[2] Department of Mechanical Engineering, Polytechnic Institute of Lisbon, 1959-007 Lisbon, Portugal
ajfa@dem.isel.ipl.pt

[3] CTS Uninova, 2829-516 Caparica, Portugal

Abstract. It is often argued that efficient collaboration is the key for successful organizations. However, achieving efficient collaboration still represents a challenge for most organizations. Often, hidden involuntary behaviors (also known as behavioral risks), threat efficient collaboration in a blink of an eye. Either by the lack of supportive models to manage sscollaboration or due to misunderstandings of what the different dimensions of collaboration are and represent, most organizations fear the engagement in collaborative approaches due the high chances of failure. In this work is proposed a heuristic model to identify organizational collaborative risks by applying social network analysis . This work aims to illustrate how organizations can benefit from the application of social network analysis in the efficient identification and management of collaborative risks. A case study illustrates the application of the proposed model in this work.

Keywords: Collaborative risks · Social network analysis · Organizational performance · Organizational business intelligence architecture · Case study

1 Introduction

It is often said that efficient collaboration is the key for success [1, 3]. According to literature, to organizations succeed in the actual complex and unpredictable market landscape they should engage in collaborative partnerships with other organizations such as universities, institutes or even their competitors [1, 3, 4]. By doing so organizations access resources, such as technologies, expertise, financial support, access new markets, just to name a few, which they alone would never have access to [1, 3, 4]. However, defining collaboration is far from being fully understood [1, 4, 5]. Research shows that there is no consensus regarding to what collaboration really means, as well as its dimensions [5, 6]. This fact represents a challenge for organizations regarding the management collaborative initiatives. Adding to this, research shows that there is a lack of efficient models to support the management of collaborative initiatives [4–6]. Both facts together

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hinder organizations from profiting the advantages that collaborative partnerships may offer. To help organizations to overcome such obstacles is proposed a heuristic model developed based on three key pillars ((1) collaborative risks, (2) social network analysis, and (3) business intelligence), that will help to identify collaborative risks, by analysing how different dynamic collaborative behaviors (also called as collaborative risks) may impact organizational outcomes. The research question can be as follows stated: *to which extent can project outcomes be impacted by the different dynamic behavioral patterns that emerge across a project lifecycle?* This analysis will be done by the application of social network analysis (SNA), that quantitatively measures data collected in several interaction tools, such as emails, chats, messages, virtual-meetings, or virtual surveys. The model was developed to be integrated into an organizational business intelligence architecture. In this work, it will be illustrated the benefits of applying SNA analysis in organizations to identify collaborative risks, and how organizations can profit from the incorporation of the model into a business intelligence architecture, transforming the integration into an artificial intelligent system that automatically collects, transforms and analysis organizational dynamic behavioral data, giving unique, meaningful, and actionable insights. This will help improve decision making activities by turning it more data informed. The proposed model acts as a supervised machine learning type, whereby the application of SNA centrality metrics algorithms, identifies, measures, and correlates organizational outcomes, with specific identified behaviors. Both aspects, give the model a novelty characteristic regarding the management of collaborative risks. Risk is translated by the different dynamic behaviors (DB) of actors in each project phase, where such different repeatable DB can be correlated to project outcomes. Collaborative risks lay in the interactions between project entities (people, organizations, or others), and not in the entities themselves. In this work, business intelligence is related to the network architecture that enables the treatment of behavioral data that contains such DBs that occurred across a phase of a given project. More concretely, it acts as a tool to accurately, precisely, and in a timely manner accomplish all the necessary steps to take insights out of dynamic data that is being created as project entities deliver a project. The indicators that will enable to quantitatively measure such DBs are SNA centrality metrics (in, out, and average degree), which are supported by strategic surveys or observations that conducts the assessment to a particular collaborative risk type that is aimed to be identified and mapped. For example, the answer provided to the question; *whom do one trusts to discuss project related matters without being afraid of retaliation*, would be a trust indicator, that quantitatively measures (individual and collective) the trust level within a project social network. This work is divided into five chapters. In Sect. 1 is done an introduction to the proposed model highlighting the motivation and importance in the organizational context. In Sect. 2 are introduced the three key pillars that support the development of the model (state of the art). In Sect. 3 is illustrated the model development and application in a typical organizational business intelligence architecture context. In Sect. 4 is presented a small case study showing the application and interpretation of results of the proposed model. In Sect. 5, are presented the conclusions and further research recommendations. The model presents a novel approach to manage collaborative risks, resulting of a multidisciplinary approach by connecting the three mentioned key pillars. This way the model adds unique value to the process of identification of organizational collaborative risks.

2 Literature Review

2.1 Collaborative Risks

Collaborative risks can be defined as risks that emerge from the several dimensions that can be found in the several definitions of collaboration [1, 4]. However, according to research, collaborative risks can be divided into four major types [6]. They are: (1) risk of critical enterprise, (2) risk in allocation of resources, (3) managerial risks, and (4) behavioral risks. Risk of critical enterprise comprises risks related to collaborative network members (people, groups, or organizations) who hold exclusive resources or competencies needed to the accomplishment of work-related tasks or activities. Risk in allocation of resources comprises risks related to how work-related tasks or activities are distributed across the different collaborative network partners, which can result in delay or bottlenecking's and thus compromise the success of an organization. Managerial risks are risks related to the structure and degree of communication and authority across all members of a given collaborative network. Finally, behavioral risks, are risks related with the different types of dynamic relationships that emerge across the several participants in a given collaborative network. In this work, the focus will be directed to behavioral risks, which by the application of social network analysis centrality metrics, will be quantitatively measured and further correlated with organizational outcomes [1, 4].

2.2 Social Network Analysis (SNA)

SNA is the process of analysing and studying social structures, by applying metrics developed based on the graph theory [1, 7]. The purpose of such analysis is to understand and explain how different social structures emerge and evolve in the environment where they do exits across time [8]. In SNA analysis, entities (people, organizations or other) are represented as dots, and the relationships between any two entities is represented by lines connecting such dots. This is the underlying basics of the graph theory. The application of SNA in organizations essentially supports the decision-making processes [1, 3]. This happens, as the process analysis how employees' behaviors may be correlated with organizational outcomes [1, 3]. The application of SNA in organizations has been exponentially growing in popularity within the latest years [1, 3–5], and can be applied in several different dimensions, such as the analysis of employee turnover and retention, individual and collective performance levels, different organizational cultures, dynamic behaviors, well-being, fraud, social cohesion, information diffusion, innovation performance, and may others [1, 4, 6, 9]. In this work, the application of social network analysis centrality metrics, such as in-degree, out-degree, density, average in-degree, closeness, betweenness, just to name a few [1, 3], are used to quantitively measure dynamic collaborative behaviors that may emerge as people carry work related tasks or activities. SNA is considered as a unique approach to measure human dynamic behavior accurately and undoubtedly, by opposition to traditional approaches essentially supported by human resources theories which introduce a huge amount of bias [1, 3, 4]. More concretely in this work, it will be used the in-degree, out-degree, and the average in-degree metrics.

2.3 Organizational Business Intelligence Architecture (BI)

Organizational busines intelligence (BI) can be defined as set of technologies and strategies to analyze business data in an efficient and data-driven way [10]. A traditional BI architecture comprises a variety of tools, methodologies, frameworks, and systematic processes, that collect, store, transform, and analyze business data, uncovering hidden, unique, and meaningful actionable information. Such information is the used by organizations essentially to understand past trends, see in real time actual trends, and predict future business trends, such as consumer behavioral patterns. Furthermore, such information is very often used by organizations to support their strategical decision-making processes [10, 11]. An efficient BI architecture comprises a dynamic organizational interconnected communication network, where information from several departments, is accessed, acquired, both, internal and external, and can be easily accessed and readable [10]. In this work, is illustrated the incorporation of the propose model into a typical organizational BI architecture, and how organizations benefit from it in the efficient identification of collaborative risks.

3 Model Development and Application

The implementation of the proposed model in this work is illustrated in Fig. 1.

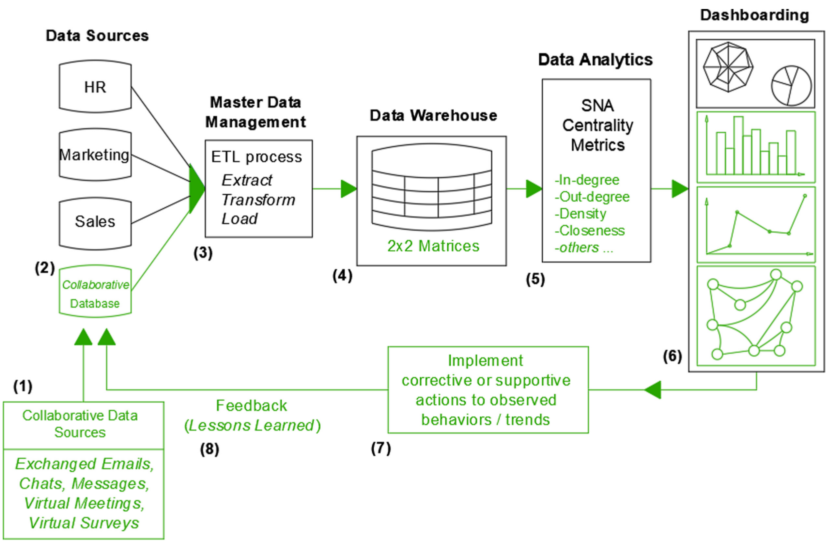

Fig. 1. Proposed model development and implementation framework.

In Fig. 1 is illustrated the integration of the proposed model into a typical organizational business intelligence architecture. According to Fig. 1, first (1), organizational behavioral data is collected through several methods, such as exchanged emails, chats conversations, chats messages, virtual meetings, or virtual surveys. Then, (2) collected data will be stored in a dedicated organizational behavioral database to further processing. Then, (3), data undergoes a ETL process (extract, transform and load), where is essentially is checked if any data is missing, if data was correctly collected, and if collected data can be used in the further step. Then, (4) data is placed in a 2 × 2 matrix form, where the relationships (interactions) between entities can be quantitatively visible, which represent the centrality degree of each entity present in network. Then, (5) SNA centrality metrics, such as in-degree, out-degree, total-degree, density, closeness, just to name a few, are applied to data stored in the 2 × 2 matrix form, to quantitatively measure organizational behavioral data across a finite period. Then, (6) the results of the quantitative analysis will be illustrated (usually dashboarded) in several forms, such as chart bars, circular graphs, trend lines, or even graphs, to provide actionable and meaningful help in decision making processes. Then, (7) according to the results obtained from the analysis to the organizational behaviors, corrective or supportive actions may be implemented. Finally, (8) after the implementation of corrective or supportive measures to quantitatively identified organizational behaviors, feedback must be given in the form of lessons learned to continuously improve the way that organizational behaviors impact organizational outputs and outcomes (continuously improvement cycle). To quantitatively measure organizational behaviors captured in collected data, a set of SNA centrality metrics can be applied as illustrated in Table 1 [12].

Table 1. Some SNA centrality metrics that can be used in the proposed model in this work.

SNA Metric	Equation	Brief description
In-degree	$C_{ID}(n_i) = \sum_j x_{ji}(1)$ C_{ID}= in degree of an entity within a graph	n = total number of entities within a graph for i = 1…, n xji = number of links coming from entity j to entity i, where i ≠ j,
Out-degree	$C_{OD}(n_i) = \sum_j x_{ji}(2)$ C_{ID}= out degree of an entity within a graph	n = total number of entities within a graph for i = 1…, n xji = number of links going from entity j to entity i, where i ≠ j,
Average In-Degree	$C_{AID}(n_i) = \frac{\sum_j x_{ji}}{n}(3)$ C_{AID}= Average In- degree of an entity within a graph	n = total number of entities within a graph for i = 1…, n xji = number of links from entity j to entity i, where i ≠ j,

4 Application Case of the Proposed Model

The following application case of the proposed model is a small extract of a larger case study conducted by an international market leader in the food and energy organization in mid-Europe in 2020. This organization (denominated Organization A) conducted a case study in his engineering department to understand the extent to which dynamic behaviors were correlated with outcomes. In Fig. 2 is illustrated part of the case study conducted by Organization A.

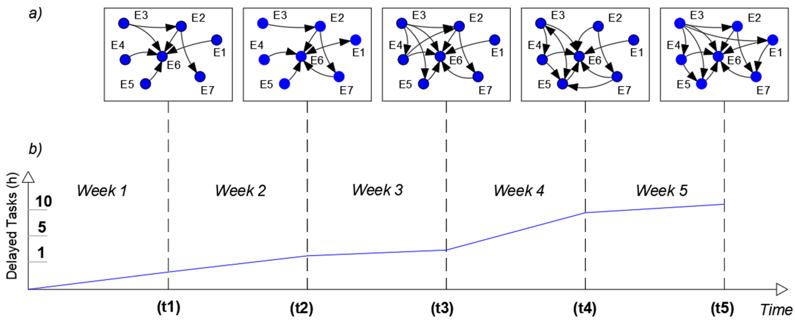

Fig. 2. Application case of the proposed model in this work (dashboarding results).

In Fig. 2 is illustrated the evolution of the organizational dynamic behaviors across five different weeks (a), and the evolution of several tasks accomplishment delays for the same period (b). Figure 2 represents point 6 of Fig. 1 (dashboarding). To understand how dynamic behaviors could impact the execution of tasks organization A conducted a study in the engineering department, (which is comprised by 7 engineers E1, E2, E7) across 5 weeks. As it can be seen in Fig. 2 a) the resulting 5 networks (for different five times – t1, t2, t3, t4, and t5) were built with data collected in virtual surveys addressed to all 7 engineers. To map the five networks in a), the following question was directed to the 7 engineers: *to whom did you turn in this last week with high frequency to ask for help or discuss any work-related matters?* This question was addressed five different times (close at the end of each week). The results obtained in the networks illustrated in a), show the answers to the respective questions. For example, applying (1) for the network of t1, engineer E6 has a degree of 5, which means that he was named by five other engineers as a resource for help and discussion regarding work related matters. For the same network applying (2), for E6, he has a degree of 0. This means that in week 1, E6 did not ask for help to any other colleagues in the engineering department. When analysing other networks, it can be seen (applying (1)), that E6 is a fundamental central piece in the engineering department because its degree, as the time moves along, goes from 5 to 5 to 6 to 6 and to 6 for t1, t2, t3, t4, and t5, respectively. This trend clearly indicates a strong dependency from the engineering team on element E6. This may represent a behavioral collaborative risk, in the sense that may introduce information bottlenecking, and ultimately the emergence of over central and extreme peripherical people in the engineering network. In fact, it can be clearly seen a certain correlation between the evolution of the different dynamic behavioral networks in Fig. 2 a), and the work-related tasks cumulative delay in Fig. 2 b). This effect can be better explained (correlated) when applying other SNA centrality metrics such as density or average in-degree. Applying (3) there is a positive evolution across time, moving from 1 to 1, 14 to 1,6 to 1,7 to 1,9 for t1, t2, t3, t4, and t5, respectively. This means that there has been an increase of dynamic interactions across the analyzed period. Simultaneously, when analysing Fig. 2b, where is illustrated the cumulative delay in hours of all work-related tasks relative to what was ahead planned, as the number of dynamic interactions increased across time, so did the cumulative delays of work-related tasks, from 1 up to almost 10 h in the engineering department. In this case, it can be concluded a strong correlation between increase in dynamic interactions of the engineering team, and the increase in the work-related tasks execution delay. Furthermore, it can also be concluded that the disproportionate centrality degree of element E6 in the different dynamic networks illustrated in Fig. 2 a), may have further contributed to the trend observed in Fig. 2 b), which clearly indicates a collaborative behavioral risk. After the conducted analysis supported by the proposed model, follow up assessment need to be undertaken to identify the underlying reasons for the uncovered dynamic behaviors illustrated in Fig. 2.

5 Conclusions and Further Research

In this work is presented a model to identify collaborative risks developed based on three key pillars ((1) collaborative risks, (2) social network analysis, and (3) business intelligence). The model applies SNA centrality metrics to quantitatively measure dynamic behaviors that emerge as organizations engage in collaborative networks. It is demonstrated the importance of SNA centrality metrics as a unique and meaningful approach to accurately measure human dynamic behavior by opposition to traditional approaches essentially supported by human resources theories which introduce a considerable amount of bias. Furthermore, it is illustrated how organizations can incorporate the model into a BI architecture, which enables organizations to collect, treat, transform, and analyze behavioral data automatically and accurately. The model can be used by organizations to identify behavioral risks and simultaneously critical success factors as it correlates identified behavioral patterns with organizational outcomes. In a managerial perspective, the model enables organizations to shift their decision-making processes from a more traditional approach based on intuition and opinions of influent people, towards a more decision-informed decision-making process. This enhances the chances of success of an organization and contributes to the achievement of sustainable competitive advantages. The model helps organizations to overcome the two main mentioned obstacles regarding collaborative initiatives (misunderstanding of what collaboration is and its dimensions, and the lack of proper models to support collaborative initiatives). This contributes to enable organizations to profit from the advantages of collaborative partnerships. In a research perspective, the model in highlights the importance of the application of SNA in organizations which may contribute to the development of further SNA centrality metrics to better map the myriad of hidden organizational collaborative behaviors. It still sheds light into the collaborative risks dimension, by enabling a deeper understand of how such collaborative risks emerge and evolve across time, which in tur may help to generate new theories regarding the development and importance of behavioral risk sin organizational outcomes. As for future research, it is recommended the use of more existing SNA centrality metrics, but not only centrality, to in a 360°-degree perspective, map the existing dynamic interactions within a group or organization as they execute work-related tasks or activities. Finally, further research should be undertaken in new methods of data collection to capture information that flows across other communication tools, such as telephone conversations, while coping with the regulatory GDPR (General Data Protection Regulation) norms and ethical aspects.

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