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A Model to Manage Organizational Collaborative Networks in a Pandemic (Covid-19) Context

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Abstract. The pandemics situation has brought unforeseen challenges to all organizations at a global scale. While some strongly profit from it, others thrive to survive or already died. In such times the bulk of leadership and management related skills, gains a disproportional importance especially for organizations where most of their workforce strongly depends on remote collaboration. Being aware of the difficulties to manage collaboration within and between teams in “normal times”, the “still” ongoing situation has only brought more complexity to organizations in that aspect. In this work is proposed a model to manage organizational remote collaborative networks in order to identify collaboration extremes (lack of collaboration, or collaborative overload) which emerges as people work together in projects or operations, developed based in three pillars (collaborative networks, social network analysis, and business intelligence). A real case study is presented to illustrate the functioning principles of the model.

Keywords: Collaborative Networks, Business Intelligence, Social Network Analysis, Pandemics (Covid-19), Organizational inclusion and performance

1 Introduction

The abrupt change in the way people around the world interact due to the pandemics, has profoundly changed. The impacts the future human relationships are far from being known [1,2]. In these times, organizations face unexpected challenges in several dimensions. For example, the need of immediate implementation of complex measures to prevent the spread of the pandemics within their internal structures (in order to protect their workforce), overloaded many organizations in financial and human resources. Simultaneously, the need of keep running the business in order to survive, demanded their employees to do the “extra-mile running” while using imagination and flexibility to keep the business as usual. In such scenario, effective and efficient collaboration within and between organizations has never been so important [3]. It is often argued that to organizations achieve sustainable competitive

advantages they must excel in performance and innovation [4]. However, research shows that one of the most efficient ways to achieve sustainable competitive advantages, is by partnering with other organizations, such as institutes, universities, or even competitors, engaging in controlled collaborative environments that enable the creation of unique value, that otherwise would not be possible [5]. Still according to research, the lack of models to manage collaborative initiatives is the major obstacle that prevented organizations back in “normal times” to engage in such partnerships with a higher frequency [5,6]. In these “new times”, for the obviously reasons, it became worst [7,8]. Latest research shows that organizational collaborative trends are deviating from the center - characterized by a balanced collaboration type -, towards the extremes [8], which may strongly negatively impact an organization’s performance and innovation capacities [5, 6]. Such extremes (known as behavioral and ambiguity risks [5, 6]), where in one side is characterized by the evolution of collaboration towards an *overload collaborative status* and in another side characterized by *poor or lack of collaboration status*, is in line with research regarding organization collaboration tendencies, which argues that negative external factors (also called external noise) - as the case of the pandemics in these “new times” -, are dangerous to organizations [9]. Research shows also that such behavioral risks can only be properly addressed by first understanding the underlying reasons, and later apply generated knowledge to future similar situations - in other words, lessons learned [5]. To contribute with a solution to the mentioned emerging and growing problem, is introduced in this work a model to support the management of organizational collaboration (also known as organizational collaborative networks), to bring collaboration trends out from the extremes towards a balanced status. The proposed model supported by three pillars (1-collaborative networks (which gives the model the theoretical background that defines collaboration within and between organizations), 2-social network analysis (which gives the model the tools and techniques to perform a quantitative analysis), and 3-business intelligence (which gives the model the capacity to operate in an autonomous (automatic) way), will analyze how organization’s employees remotely collaborate in the “new times” by analysing their dynamic interactions in four interrelated dimensions.

2 Literature Review

2.1 Collaborative Networks

Collaborative networks represent different entities, such as people, or organizations that share resources to achieve common and compatible goals, exchange information, adjust and plan activities [10]. Collaboration means working together in a shared creation approach [10]. It comprises the sharing of responsibilities, risks, and rewards, as participants mutually engage to solve a problem or challenge [10]. Collaboration is for example when experts from different organizations or departments, work together to develop a new service or product in an environment where natural coordination exists, and also a continuously seeking process of new ideas and insights, fueled with psychological safety and meaningful discussions, rather than only working under a

perfect balanced environment [10]. Factors such as reciprocity (feedback regarding a particular subject), trust, and interlocking directorates are part of collaboration [10, 11]. Research shows that efficient collaboration contributes to better adapt to change, enables to create strategic inter-organizational networks, and increases flexibility to better face disruptive changes [12]. In the model presented in this work collaboration is assumed the “joint work level” existing between organizations employees.

2.2 Social Network Analysis

Social network analysis (SNA) studies social structures applying a variety of SNA centrality metrics (CM) enabling to the understand how they emerge and evolve in the environment where they exist [13]. SNA centrality metrics (SNACm) can be applied in organizations to quantitatively analyze collaborative patterns, talent shortages, cultural fit, information exchange, unethical behaviors, employee turnover, fraud, and so on [14]. SNACm play a fundamental role in understanding the importance of organizational social capital, and therefore is being continuously incorporated into organizational human resources processes and frameworks, as well in organizational risk management departments [15, 16]. Literature shows that the application of SNACm enabled to identify three critical informal networks ((1) communication – uncovering who interacts with whom, (2) advice- uncovering who gives or asks advice, and (3) trust - uncovering who trusts whom) that exist in any organization regardless of type or size, and play an important role in performance and innovation [17]. SNACm enables the identification of key informal roles, such as central connectors (people who play a central role within an organizational network), peripheral people (people who either intentionally or not, are not integrated within an organizational network), brokers (people who connect different organizational departments or organizations), and energizers (people who positively influence others around them) that exist in organizations [18]. In project management SNACm can identify project critical success factors regarding the dynamic behavior of project people across the phases of a project lifecycle [16]. SNACm such as in-degree, out-degree, closeness, betweenness, are applied to identify organizational hidden behavioral patterns, and growing in popularity [16]. Research shows that such CM are often correlated with an entity’s importance, prestige, and influence, and can be an index of a network’s potential activity, communication, control and spreadness [19, 20, 21, 18, 16]. In this work the application of SNACm enables to quantitatively measure the amount of informal behavioral patterns within an organizational network.

2.3 Business Intelligence

Business intelligence (BI) are strategies, frameworks, processes, tools, technologies and concepts employed by organizations to analyze business data, to accelerate and optimize the decision-making processes [22,23,24]. A typical BI architecture collects row data (data from different applications or platforms in several formats) from several sources, such as finance, engineering, human resources, sales, or other. Then,

collected data is cleaned and organizing by a process called ETL (extract, load and transform) which normalizes collected data into readable and editable form. Then, data will be analyzed - usually by the application of mathematical and statistical tools and techniques. Finally analyzed data is displayed in visual meaningful representations (usually called data dashboarding), such as graphs, tables, or line trends (usually in the form of critical success factors and key performance indicators), so that organizations can perform the decision-making process in a more data-informed way (also known as a less biased way). Incorporating a BI into an organization's structure may provide unique benefits regarding the measuring, understanding, and correlation of past events with outcomes (usually known as descriptive analysis), and how these can help manage ongoing situations (usually known as predictive analysis), while parallelly identifying future business trends and suggesting strategical moves (usually known as prescriptive analysis) [23,24,25]. In this work the proposed model to manage organizational collaborative networks includes the incorporation of an organizational BI architecture to provide all the above-mentioned benefits to organizations regarding the overall data analysis process.

3 Development and Implementation of the Proposed Model

The proposed model in this work illustrated in Fig. 1 was developed based on three pillars and will analyze how organization's employees remotely collaborate to accomplish organization's tasks and activities.

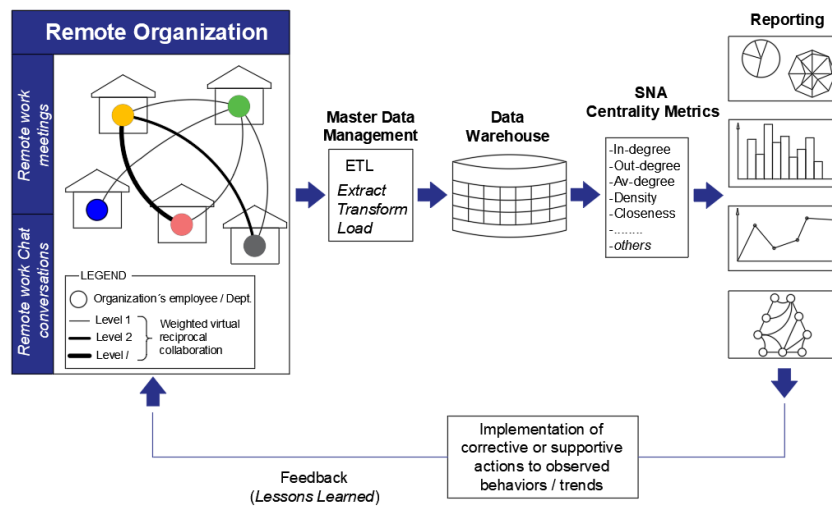


Fig. 1. Proposed model implementation framework and application methodology.

The model illustrated in Fig. 1 will analyze how remote dynamic interactions emerge and evolve across time by measuring four different but interrelated dimensions ((1) attendance degree in work-remote meetings, (2) amount of time spoken in work-remote meetings, (3) number of communicated people through work-chats

conversations, and (4) the respective amount of time spent in work-chats conversations). Such dimensions were chosen because most of them represent the core of dynamic interactions between employees of an organization in a remote context. The implementation and application of the propose model follows the following methodology: First, data from two different sources ((1) remote work meetings), and (2) remote work chats conversations) will be collected and prepared (extracted, transformed, and loaded) to be stored into a master data warehouse. Then, data will be quantitatively measured by the application of SNAcm. Then, analyzed data will be outputted in graphic or tabular form o be properly interpreted and extracted hidden behavioral patterns that may put at risk collaboration and thus threaten the organizations goals and objectives. Finally, accurate quantitatively measures can be applied to adjust or support uncovered behavioral patterns. To quantify the amount of dynamic remote interaction between employees of an organization, SNAcm will be applied as illustrated in Table 1.

Table 1. Proposed model SNAcm

Sources	SNA centrality Metrics & Description
Remote work meetings	<p><u>Objective 1</u>: Measure the attendance degree in work-remote meetings. <u>Objective 2</u>: Measure the amount of time spoken in work-remote meetings. <u>Data</u>: In each remote work meeting record the number of participants and the respective spoken time. <u>SNAcm</u>: For objective 1 the simple sum (recorded attendance) will be applied. For objective 2 the CM weighted in-degree [19] (1) will be applied.</p> $I_{DW}(n_i) = \sum_j x_{ji} \quad (1)$ <p>Where: I_{DW}= weighted in-degree of an organization employee regarding remote working meetings attendance. Weights are classified in 3 levels (Level 1, 2, and 3). n = total number of work remote meetings for $i = 1 \dots, n$. x_{ji} = number of links from entity j to entity i, where $i \neq j$, which represents the direct attachment from a given employee to a given remote work meeting.</p>
Remote work-chat conversations	<p><u>Objective 1</u>: Measure the number of communicated people through work-chats conversations. <u>Objective 2</u>: Measure the respective amount of time spent in work-chats conversations. <u>Data</u>: In each remote chat conversation record the number of different conversations and the respective chatted time. <u>SNAcm</u>: For objectives 1 and 2 the simple sum (in-degree) [19] will be applied. <u>Additional</u>: To characterize the remote work social network's structure the SNAcm average in-degree will be applied [19] (2).</p> $I_{Av}(N) = \frac{\sum_{i=1}^n x_{ji}}{n} \quad (2)$ <p>Where: I_{Av}= average in-degree of given social network (remote work social network). n = total number of participants in remote chat work conversations for $i = 1 \dots, n$ x_{ji} = number of links from entity j to entity i, where $i \neq j$, and vice-versa. N = all elements of a remote work social network.</p>

3.1 Real Case Application of the Proposed Model in this Work

A food & beverage market leader organization (named as organization A due to legal and anonymous reasons) applied the propose model in this work to understand how collaboration in the “new times” affected by the still ongoing pandemics, has been evolving across their 16 elements of the engineering department. For this matter organization A implemented the proposed model into a BI architecture as illustrated in Fig. 1, and collected data according to Table 1 between March and May of 2020. All 16 elements agreed to participate in the study complying with the general GDPR (General Data Protection Regulation at <https://gdpr-info.eu/>) rules. Within the mentioned period of time 12 work meetings (coined as virtual weekly *coffee-breaks*) have been accomplished to discuss organizational matters and to promote the interaction between employees who were exclusively working remotely. In Table 2 are illustrated the results regarding the dimension remote work meetings between March and May 2020 by applying the simple sum and (2) according to Table 1.

Table 2. Results for virtual work meetings between March and May 2020

<i>E</i>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
<i>VM</i>	9	8	12	10	11	12	9	12	11	8	7	12	9	11	11	8
<i>ST</i>	1	1	1	1	1	1	1	3	3	2	2	2	1	1	1	1

In Table 2 *E* stands for employee number, *VM* stands for total number of attended work virtual meetings, and *ST* stands for spoken time level. There are 3 *ST* levels (L1(yellow): 0- 50 min., L2 (green): 51-100 min., and L3 (orange): > 101 min.). According to Table 2, 70% of the 16 engineers only spoke a total time between 0 and 50 minutes, while 13 % spoke > 101 minutes in all remote meetings. Such values represent an unbalanced social network regarding collaboration measured in work spoken time. Such results suggest a deeper analysis to better understand how such collaborative behavior emerged and evolved across time. This is illustrated in Fig. 2.

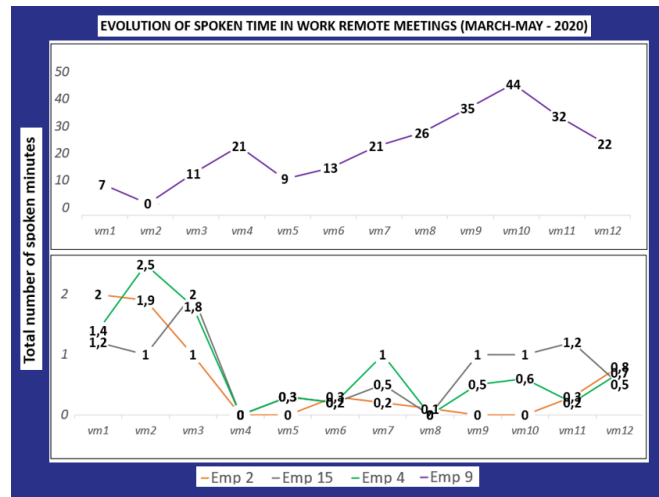


Fig. 2. Spoken time longitudinal evolution in virtual meetings for employees 2, 15, 4 and 9.

In Fig. 2 is illustrated the evolution of spoken time in each remote work meeting $vm(i)$, (virtual meeting) for elements 2, 15, 4 and 9, which correspond to the highest values observed in Table 2 (element 9) and to the lowest values observed in Table 2 (elements 2, 4, and 15). As it can be seen in the upper side of Fig. 2 element 9 had a total of 241 spoken minutes, contrasting with the 27 spoken minutes of elements 2, 15, 4 together. In Fig. 2, can also be seen that from $vm3$ to $vm4$ there has been an abrupt change in the behaviors of elements 2, 4, and 15, which simultaneously coincides with the almost exponential growth of element 9, specially from $vm5$ onwards. These behaviors may represent a risk of collaboration between the 16 engineers of organization A, which if not properly managed it may evolve either to an overload collaborative status (namely by most participative elements, such as element 8 and 9) or to a poor or even a lack of collaboration status (namely by less participative elements such as 2, 4, and 15). If such observed trend keeps evolving across time, it still may evolve to collaborative bottlenecks (emerging in elements with disproportional participative levels) or even lead to the emergence of organizational silos (weak collaborative group vs high collaborative group). In Fig. 3 are illustrated the results regarding the second dimension (remote work-chat conversations), by the application of the simple sum and (2), according to Table 1.

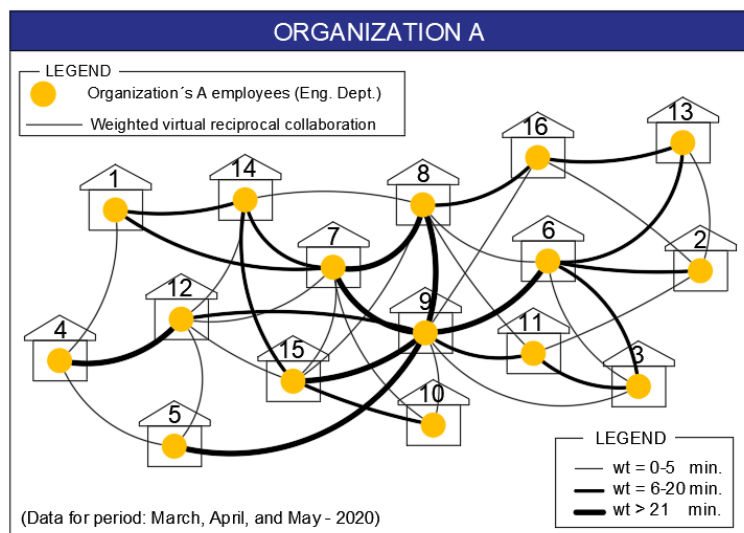


Fig.3. Chat communication network between March and May 2020.

In Fig. 3 is illustrated the chat communication network between the 16 engineering elements of organization A, that took place between March and May 2020. As it can be seen in the legend of Fig. 3, the weighted lines that connect the different 16 elements of organization A, represent who chatted with who (given by the lines between any give two elements), and how much it communicated (represented by the thickness of the respective lines). For example, it can clearly be seen that element 9 is by far the most central within the chat communication network, with an in-degree of 10 (which means that he communicated with 10 different elements), and a total

amount of communicating time (wt, which is essentially writing) of 458 minutes. The individual results regarding Fig. 3, are illustrated in Table 3.

Table 3. Results for virtual chat conversations between March and May 2020

<i>E</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>10</i>	<i>11</i>	<i>12</i>	<i>13</i>	<i>14</i>	<i>15</i>	<i>16</i>
<i>TC</i>	3	5	4	3	3	7	7	7	10	2	4	6	3	5	6	4
<i>CT</i>	32	21	36	48	68	212	254	198	458	28	19	68	56	97	208	77

In Table 3 *E* stands for employee, *TC* stands for number of people chatted to in virtual communication, and *CT* stands for total number of minutes chatted in virtual communications. The average in-degree (applying (2)) for this network is 5, which means that in average each element had communicate with 5 different colleagues. However, this number is far from 15, which represents the full balanced average in-degree of each element if all elements had communicated among themselves. It can also be seen that 50% of the engineering team (yellow marked) is under the calculated average in-degree, and that no element has reached the ideal number of 15. The results in Table 3 are clearly aligned with the results observed in the previous dimension - remote work meetings -, where element 9 has again an extreme central position, whereas elements 2 and 4, but not only, are in the other extreme, which in other words means, being very peripheral.

4 Conclusions and Further Developments

As demonstrated across this work the proposed model is an efficient strategy to answer the following research question: “how is collaboration evolving across time, between organizations employees that exclusively work remotely to accomplish organizational tasks and activities?”. Given the pandemic’s scenario worldwide, the proposed model enables organizations to uncover hidden behavioral patterns that emerge and evolve across time that may threaten collaboration. By doing so, the propose model addresses behavioral and ambiguity risk types, as suggested by [5, 6, 16, 26, 27]. The model enables organizations to quantify past collaborative evolutions which allows them to learn how dynamic behaviors can be correlated with outcomes - in other words, lesson learned. This in turn, enables organizations to in a more data-informed way, identify critical success and failure collaborative factors, which they later can use to guide and monitor future collaborative initiatives. The implementation of the proposed model in organizations implies first to create the necessary “virtual space” to enable an efficient functioning in all model’s stages (data collection, transforming, analyzing and dashboarding). This step (implementation of a BI architecture), translates a boost in the digital transformation process, in transferring many of the manual organization operations and procedures into digital ones. This step also enables organizations to perform according to GDPR guidelines - and for the propose model itself - it enables a non-invasive, and full bias-free data treatment, by opposition to traditional performance management systems, such as pulse surveys conducted by organizations to evaluate collaboration and satisfaction levels. The proposed model positively contributes to the sustainability triple bottom line

(economic, social, and environmental), by enabling organizations to minimize or eliminate risks regarding collaboration in formal and informal organizational networks, which in turn contributes to optimize and improve resources usage, leading to leaner organizational business strategies. Nevertheless, the implementation and application of the proposed model requires organizations to be flexible and open to adopt a new way of working. This may become a challenge to organizations, due to the power that resistance to change may offer, usually hidden in organizational informal networks. The proposed model does not capture all interactions between organization's employees, such as those that happen in work email exchange and phone calls. Therefore, new SNA centrality metrics - but also dispersion- should be developed, and other existing SNA metrics should be applied in order to better mold a 360 approach towards the identification of risk collaborative behavioral patterns. In order to clear identify the differences between "now and then" (in covid-19 rimes and after covid-19 times) regarding collaborative initiatives, is suggested that organizations apply the proposed model in "both times". This will lead to better understand the impacts that covid-19 has in collaborative initiatives. Finally, because some employees might not agree with such vast analysis of relational data, further research should be conducted in finding ways to capture such employee's relational data without going against employees legal and privacy aspects.

References

1. Harris, Timothy F. and Yelowitz, Aaron and Courtemanche, Charles, Did COVID-19 Change Life Insurance Offerings? IZA Discussion Paper No. 13912, Available at SSRN: <https://ssrn.com/abstract=3743136>. (Accessed on 08 March 2021)
2. Marois G, Muttarak R, Scherbov S Assessing the potential impact of COVID-19 on life expectancy. PLOS ONE 15(9), (2020)
3. Hamouche S. COVID-19 and employees' mental health: stressors, moderators, and agenda for organizational actions. Emerald Open Research, 2:15 (2020)
4. Friar, J. Competitive Advantage Through Product Performance Innovation in a Competitive Market. *J. Prod. Innov. Manag*, 12, 33–42. (2003)
5. Nunes, M.; Abreu, A. Managing Open Innovation Project Risks Based on a Social Network Analysis Perspective. *Sustainability*, 12, 3132 (2020)
6. Nunes M., Abreu A. A Model to Support OI Collaborative Risks Applying Social Network Analysis. In: Camarinha-Matos L.M., Afsarmanesh H., Ortiz A. (eds) Boosting Collaborative Networks 4.0. PRO-VE 2020. IFIP Advances in Information and Communication Technology, vol 598. Springer, Cham.
7. Tannenbaum SI, Traylor AM, Thomas EJ, et al. Managing teamwork in the face of pandemic: evidence-based tips *BMJ Quality & Safety*; 30:59-63 (2021)
8. Kaushik, M. & Guleria, N. The Impact of Pandemic COVID -19 in Workplace. *European Journal of Business and Management* Vol.12, No.15, (2020)
9. Cross, R.; Rebele, R.; Grant, A. Collaborative Overload. *Harv. Bus. Rev.* 94, 74–79 (2016)
10. Camarinha-Matos, Luis & Afsarmanesh, Hamideh. Collaborative Networks: Value creation in a knowledge society. International Federation for Information Processing Digital Library; Knowledge Enterprise: Intelligent Strategies in Product Design, Manufacturing, and Management (2006). https://doi.org/10.1007/0-387-34403-9_4

11. Rindfleisch, A. Organizational Trust and Interfirm Cooperation: An Examination of Horizontal Versus Vertical Alliances. *Marketing Letters* 11, 81–95 (2000).
12. Schalk, René & Curşeu, Petru. Cooperation in organizations. *Journal of Managerial Psychology*. 25. 453–459. (2010).
13. Abreu, A., & Nunes, M. Model to Estimate the Project Outcome's Likelihood Based on Social Networks Analysis. *KnE Engineering*, 5(6), 299–313, (2020)
14. Blacker, K; McConnell, P. *People Risk Management: A Practical Approach to Managing the Human Factors That Could Harm Your Business*; Kogan Page Publishers, CPI Group (UK), Ltd, Croydon. (2015).
15. Krivkovich, A.; Levy, C. Managing the people side of risk. McKinsey Global Institute. 2015. Available online: <https://www.mckinsey.com/business-functions/risk/our-insights/managing-the-people-side-of-risk> (accessed on 15 February 2019).
16. Nunes, M.; Abreu, A. Applying Social Network Analysis to Identify Project Critical Success Factors. *Sustainability*, 12, 1503 (2020)
17. Krackhardt, D.; Hanson, J. Informal Networks the Company behind the Charts; Harvard College Review: Massachusetts, USA, 1993. Available online: <https://www.andrew.cmu.edu/user/krack/documents/pubs/1993/1993%20Informal%20Networks.pdf> (accessed on 5 March 2018)
18. Cross, R.; Parker, A. *The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations*; Harvard Business School Press: Boston, MA, USA, (2004).
19. Wasserman, S.; Faust, K. *Social Network Analysis in the Social and Behavioral Sciences*. In *Social Network Analysis: Methods and Applications*; Publisher: Cambridge University Press; Cambridge, USA. 1994; pp. 1–27, ISBN 9780521387071.
20. Liaquat, H.; Wu, A.; Choi, B. Measuring Coordination through Social Networks. In *Proceedings of the ICIS 2006 Proceedings*, Milwaukee, Wisconsin, USA, 10–13 December (2006).
21. Freeman, L. Centrality in social networks conceptual clarification. *Soc. Netw.*, 1, 215–239. (1979)
22. Rouhani, Saeed & Asgari, Sara & Mirhosseini, Vahid. (2012). Review Study: Business Intelligence Concepts and Approaches. *American Journal of Scientific Research* ISSN 1450-223X Issue 50 pp. 62-75. (2012)
23. Rad, R. *Microsoft SQL Server Business Intelligence Development Beginner's Guide*. 2014, Packt Publishing, Livery Place, 35 Livery Street Birmingham B3 2PB, UK (2014)
24. Nedim D. & Clare S. Measuring the Success of Changes to Existing Business Intelligence Solutions to Improve Business Intelligence Reporting. 10th International Conference on Research and Practical Issues of Enterprise Information Systems (CONFENIS), Vienna, Austria. pp.225-236 (2016).
25. Ponnambalam, Kumaran. *Business Analytics Foundations: Descriptive, Exploratory, and Explanatory Analytics*. (Available online at: <https://www.linkedin.com/learning/business-analytics-foundations-descriptive-exploratory-and-explanatory-analytics/stages-of-business-analytics?u=77012418>. Accessed on 29 March 2020).
26. Nunes, M.; Abreu, A.; Saraiva, C. Identifying Project Corporate Behavioral Risks to Support Long-Term Sustainable Cooperative Partnerships. *Sustainability*, 13, 6347 (2021).
27. Nunes, M.; Abreu, A.; Saraiva, C. A Model to Manage Cooperative Project Risks to Create Knowledge and Drive Sustainable Business. *Sustainability*, 13, 5798 (2021)