Identification of key actors in Industry 4.0 informal R&D network

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Abstract

INTRODUCTION: Industry 4.0 is a concept covering various research areas. Their development depends on the cooperation among several stakeholders, particularly public R&D (Research and Development) organisations.
OBJECTIVES: This article aims to provide a mapping of informal strategic R&D partnerships of public R&D organisations in an ambiguously defined area of Industry 4.0.
METHODS: Scientific collaboration mapping method based on self-identification is used. Moreover, social network analysis is used to discuss patterns and specific characteristics of this network. Empirical data are gathered through a questionnaire survey focused on managers of R&D teams in the Slovak Republic.
RESULTS: The resulting network of public R&D organisations operating in the field of Industry 4.0 in the Slovak Republic is connected, though characterised by low density. Intra-regional cooperation prevailed only in the region of the capital city. In other regions, cross-regional cooperation was dominant. Most cooperations occur between universities; cooperation between faculties and within one faculty is less frequent. Key teams of the network were identified based on their performance in three selected indicators of centrality. Three of them represented the first layer or core of the network.
CONCLUSION: Within the network, active actors with a high number of cooperation and those located in its network centre who can support knowledge transfer across the identified R&D network are crucial. Our results confirmed that several variables are important to creating new collaborations and thus not limited to geographical proximity, institutional affinity and size of the workplace.

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1. Introduction

In the global community nowadays, cooperation and teamwork are emphasized, not competition and individuality (Beaver, 2001). The modern scientific world is characterised by many self-organised networks, which are created by researchers, i.e. a bottom–up approach that aims to share knowledge, experience, etc. (Royal Society, 2011).

As new scientific disciplines develop and emerge, the need for cooperation becomes more urgent. These scientific disciplines are often characterised by great multidisciplinarity. According to Wowk et al. (2017), interdisciplinary and transdisciplinary research associated with the so-called co-production of knowledge with user communities has the greatest impact and use for practice. Industry 4.0 is one of the multidisciplinary fields that is not specifically defined in research despite its growing importance (Smit et al., 2016).

The 'Industrie 4.0' concept was first introduced in Germany following the national High-Tech Strategy in 2006. This concept was essentially a set of technological changes in production and the establishment of priorities for a policy framework to maintain the global competitiveness of the German industry (Smit et al., 2016). Industry 4.0 is mainly associated with automation and its means, data exchange in manufacturing technologies including cyber-physical systems, the Internet of things, big data, augmented reality, additive manufacturing, simulation, horizontal and vertical system integration, robotics and cloud (Tay et al., 2018). Culot et al. (2020) and Nosalska et al. (2020) also emphasised the complexity, multidisciplinarity and multidimensionality of the Industry 4.0 concept. They addressed the issue of defining Industry 4.0 through a review of scientific studies. Because the concept was not only scientifically but also politically motivated, Beier et al. (2020) perceived Industry 4.0 as a socio-technical concept or a collective term of different developments. The implementation of Industry 4.0 by industry is essential, though research activities are an important element of implementation strategies (National Academy of Science and Engineering, 2013).

In this article, we present a novel approach to mapping a network of scientific collaborations, focusing on public R&D organisations in the field of Industry 4.0 within one country. This approach is based on the self-identification of the network, proceeding from its core to other layers using the snowball approach. The specific characteristics of the resulting network are discussed through network analysis methods. The key actors of the network are identified based on their values of selected indicators of centrality.

2. Literature review

2.1. Benefits of scientific collaboration

Cooperation in research generates numerous benefits for participating research institutions, though it indirectly impacts other research organisations, businesses and society in various ways. Collaboration increases research quality and efficiency, enables cost-sharing and enhances research tasks and expertise. Collaboration can help raise funds, providing access to facilities, equipment and networks, and address large-scale research issues (Royal Company, 2011). Aldieri et al. (2020) stated that improving an organisation's research quality not only benefits the organisation but also creates important externalities that are disseminated through scientific research cooperation.

Many studies explored research cooperation, which often focuses on cooperation within specific fields, such as mathematical research (Reji-Manuel, 2018); science and engineering (Lee et al., 2012); groups of disciplines, including agriculture, engineering, public health and

computing (Muriithi et al., 2018); microbiology (Seglen-Aksnes, 2000), laser science and technology (Garg-Padhi, 2001); and computer science (Liang et al., 2001).

Certain studies have provided interesting findings on the relationship between research collaboration and research performance. A study based on data from 241 universities in Russia over 2 years found that more external collaborations had a positive effect on university performance as measured by the number of citations (Aldieri et al., 2020). Contandriopoulos et al. (2016) examined the collaborations of 73 researchers in an academic research network in Canada and found a significant relationship between a researcher's structural position in the network and his/her performance. Particularly, the betweenness centrality and h-index exhibited a high correlation. Degree and betweenness centrality indicators were also highly correlated (Contandriopoulos et al., 2016).

Boozeman-Corley (2004) analysed 451 researchers from academic research centres in the United States. They found that researchers who received higher grants had more collaborations and were also more 'cosmopolitan' compared with those who received lower grants. However, the study also found that most researchers tend to collaborate with their peers in their workgroup. Each collaboration type has different benefits and increases knowledge to varying degrees (Boozeman-Corley, 2004).

A study analysing 22 scientific networks in Austria showed that a high level of collaboration is strongly correlated with a low level of quality variability within each network. The study was not based on co-authorship data but data on collaboration on various sub-projects funded by the Austrian Science Fund. According to the authors, their finding is due to the peer review process, which plays an important role. '…in networks where there is strong internal peer review, quality is controlled more and quality is more uniform. Where peer review is weak therefore, there is greater variability in research output quality…' (Rigby-Edler, 2005, p. 792).

A US study of a government-funded research network generated an interesting finding of the benefits of multidisciplinarity. Two teams with different characteristics were compared within this network. The first team was comprised of scientists with a similar background, working in a well-established paradigm, and the second team included scientists with diverse professional backgrounds, working on new topics. The study concluded that cooperation (participation in the network) increased the productivity of both teams, though the increase was more pronounced in the second team with a heterogeneous composition of researchers (Porac et al., 2004).

Lee et al. (2012) identified collaboration strategies using a panel of 23 R&D organisations in Korea over 10 years. They found that R&D institutions with high productivity belonged to the group where networks had lower efficiency and betweenness centrality of entities but higher density, closeness and eigenvector centrality, i.e.

maintaining intensive relationships with existing partners (Lee et al., 2012).

Lotrecchiano et al. (2016) used the scoping review method to analyse the motives and threats to cooperation. They included 142 scientific articles on research cooperation (covering more than 60 years) in the review process. The authors created six domains of motivation and threats to cooperation, namely resource acquisition, advancing science, building relationships, knowledge transfer, recognition and reward, and maintenance of beliefs. Within these domains, they determined 51 motivation and threat indicators (Lotrecchiano et al., 2016).

2.2. Co-authorship vs. other approaches

Many studies focusing on research collaboration are based on co-authorship data of individual researchers' publications. They follow collaborations within the country, e.g. Korea (Lee et al., 2012), India (Reji-Manuel, 2018), the US (Porac et al., 2004) and Norway (Seglen-Aksnes, 2000). Others focus on multiple countries simultaneously (Aldieri et al., 2018; Zitt et al., 2000). Mapping collaborations through co-authorship of scientific publications has certain limitations. Particularly, they allow mapping of only formalised cooperation, generating scientific outputs (publications), and do not provide information about cooperation quality. This approach also does not identify whether the cooperation is important within the network, long-term and a 'gift authorship'. Under gift authorship, co-authorship is 'given' to a person who did not participate in the publication, which may be due to various reasons. Additionally, the approach focuses only on papers in scientific journals included in databases (such as Scopus and WoS), although the results of R&D cooperation show other outputs, such as patents, software, prototypes and books, especially in technical departments.

Self-identification approaches can better capture informal collaborations. This approach was used, e.g. in a study analysing research collaboration in the US (Boozeman-Corley, 2004) using data from 451 scientists and engineers working in academic research centres in the US. The study focused on multidisciplinary working groups and research areas. When mapping collaborations, respondents reported the number of researchers or postgraduate students with whom they had conducted research collaboration in the last 12 months. Muriithi et al. (2018) conducted a study on 246 researchers working in four different disciplines within the four most important universities in Kenya. The respondents in this study indicated whether they had been involved in collaboration in the last 10 years ('yes' or 'no' as an answer). Contandriopoulos et al.'s (2016) study used data from scientists' academic curriculum vitae (CV) available on the Canadian Common CV platform which collects CVs of all researchers in the same format. The network of collaborations was created based on the names of other researchers that appeared in the researchers' biography. The co-authorship of publications and collaborations on ongoing grants and other outputs, such as the so-called co-presented communications, were also included. Each type of research collaboration was assigned a duration as a subjective determination, e.g. 1 year before the start of communication or 2 years before the publication of the article.

3. Data collection and methodology

3.1. Scientific collaboration mapping

The research network was created based on data obtained from a questionnaire survey. The questionnaire survey was conducted on a sample of 20 respondents, who were leaders of these research teams.

The process of network creation began with identifying the network core. These first-level teams were identified through data mining of excellent international research projects funded by Horizon 2020 to identify internationally successful teams. Data mining focused on the identification of projects in which a partner from Slovakia participated. The description of the project included keywords related to Industry 4.0. These keywords were derived from priority areas defined in several strategic materials approved in Slovakia, namely 'Industry 4.0', 'robot', 'IoT', 'Internet of things', 'industrial internet', 'simulation', 'artificial intelligence', 'augmented reality', 'cyber', 'cyber security', 'cloud', 'big data', 'additive manufacturing' and '3D printing' (Balog-Herčko, 2020).

Four R&D teams were identified that were above-average successful in terms of the number of approved Horizon 2020 projects in which they participated. These teams were identified as the first level of cooperation or first layer of the network. Subsequently, the network was expanded using the snowball approach. The first-level R&D teams were approached using a questionnaire survey. They were asked to identify other teams of public R&D organisations with which they cooperate and plan to develop and strengthen this cooperation in the long term and whom they consider strategic and above-average partners. Thus, we captured informal collaborations that were not institutionalised, resulting in the identification of other R&D teams that represented the second-level (layer) of the R&D network. A questionnaire survey was also administered to these R&D teams. In case that the second-level teams identified a team not included in the first or second layer, they were considered as third-level of the R&D network. In most cases, teams cooperated within the first and second levels of the network.

The final Industry 4.0 network consisted of four first-level teams, 17 second-level teams, and 11 third-level teams. These 32 teams are located at three technical

universities, the Institute of Informatics of the Slovak Academy of Sciences (SAS) and one university focused on non-technical areas.

3.2. Network analysis

The data obtained from the questionnaire survey were visualised and processed using the Gephi software. In addition to visualising the network, this process enabled the calculation of statistical indicators of the network.

The position of individual actors of the R&D network is determined in this study using the widely used three indicators: degree, closeness and betweenness centrality (Giustolisi et al., 2020).

The degree indicator considers in- and out-degree centrality. The indicator of in-degree centrality for a certain actor provides information on how often other network actors approached this actor and how many actors mentioned his/her as a partner for research cooperation. Thus, the importance of an actor increases depending on how often he/she has been identified as significant by other actors or nodes of the network. Conversely, within the out-degree centrality, actors (nodes) who identified several other strategic partners are more important. Our network analysis focused on in-degree centrality for two reasons. First, the in-degree centrality indicator has higher objectivity and informative value compared with the out-degree centrality indicator because our data were collected from a questionnaire survey in which respondents were asked to indicate their strategic partners. We are aware that the term 'strategic partner' may be subject to slightly different interpretations by respondents and may overestimate or underestimate the number of partners. The number of partners who mentioned a certain point as their strategic partner indicates the most important and sought-after partner in the network from the perspective of R&D organisations. Second, only the first- and second-level layers of the network were involved in the questionnaire survey. The third level of the network was not addressed through a questionnaire and therefore had an out-degree of 0 .

Collaborations that took place in several technological domains of the Industry 4.0 were given a higher weight. For example, if department A cooperated with department B in the domains of advanced robotics, augmented reality and artificial intelligence, then their cooperation was assigned a weight of 3. Therefore, the value of weight represents important information as it indicates the extent and intensity of cooperation between two entities. Solely monitoring the number of collaborations is important,

though collaborations with higher weights can have a much higher impact than collaborations with lower weight (Opsahl-Agneessens-Skvoretz, 2010). In this study, the weight of individual collaborations was considered by using the weighted in-degree indicator.

Closeness and betweenness centrality were analysed comprehensively to gain a deeper insight into the importance of individual actors within the network. Obtaining this understanding would not be possible by focusing only on the number of cooperation of individual actors. The actor (node) that can be reached through the lowest number of 'paths', is the node with the highest closeness centrality. Being reached through the lowest number of paths indicated that for each actor of the network, the node is most easily achievable. Thus, the closeness centrality indicator shows the closeness of the node to all other nodes of the network. Lee et al. (2012) also stated that the closeness centrality indicator expresses the ability of a node (actor) to control network communication.

Betweenness centrality assesses the extent to which a given node is located on the shortest path between two other nodes within the network. The actor with the highest betweenness centrality is a link within the network. Monitoring the indicator of betweenness centrality is important because if someone has less cooperation but higher betweenness centrality, then he/she has a central 'bridge' position in the network (Contandriopoulos et al., 2016). 'The more people depend on a user to make connections with other people, the higher that user's betweenness centrality becomes' (Hansen, 2020, p. 168).

4. Results

4.1. Social network analysis

Figure 1 below shows the cooperation of all identified domestic R&D teams within the Industry 4.0 concept. Ninety-one links representing different types of cooperation were identified between individual R&D teams. The result is a continuous network, within which paths connect nodes to one another. This connection indicates the complementarity and interconnectedness of individual technological areas of the Industry 4.0 concept.
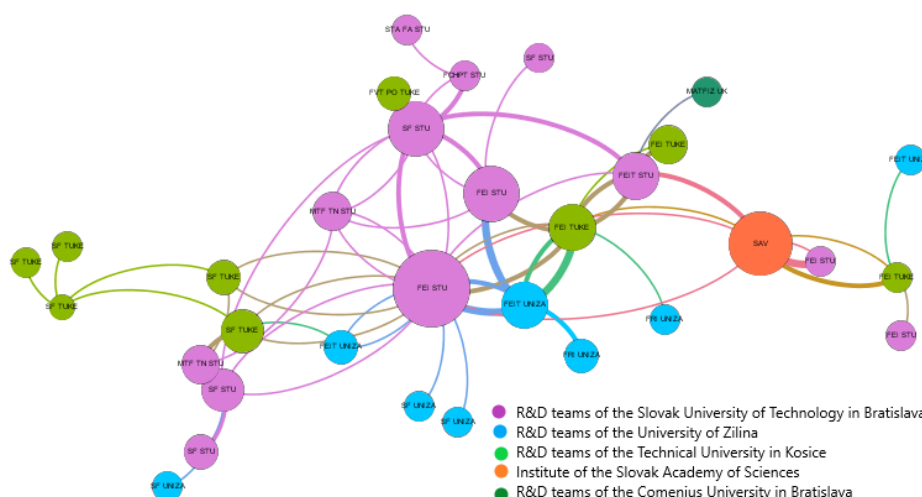
Figure 1. Network of collaborations of domestic R&D teams in Industry 4.0
Source: Processed in the Gephi program based on the data from a questionnaire survey.
Note: The colour and thickness of the lines are determined by the node to which the cooperation is directed and the weight of the cooperation, respectively.

The overall cooperation level represented by network density between individual teams is low. The network density indicator shows the number of potential connections that have taken place. If all possible collaborations were realised, then the value of the indicator would be 1. Within a denser network, a presumption of better sharing of information and knowledge exists. Thus, the aim is to achieve the highest possible value of this indicator. In our case, the network density reaches an extremely low value (0.092), indicating a large space for further improvements in collaborations. For example, the network density of research organisations in Korea was 0.25 (Lee et al., 2012)

On average, one R&D team cooperated with almost three others; the value of the average degree was 2.8. The average degree indicator does not consider multiple cooperations in individual technological domains. The average weighted degree indicator includes multiple cooperations while assigning a higher weight to cooperations that took place in several domains simultaneously. The value of the average weighted degree was 3.7.

AVERAGE WEIGHTED DEGREE	3,7

4.2. Geographical dimension

Domestic teams of public R&D organisations included in the network operated in various regions of Slovakia. The capital of the Slovak Republic had the highest number of teams and researchers working within these teams, followed by the regions of Žilina and Košice with the same number of R&D teams. Several teams were located in two smaller regions near the two largest cities in Slovakia, namely Trnava (near Bratislava) and Prešov (near Košice). The cooperation between the individual teams of public R&D organisations was not regionally homogeneously distributed. For teams located within the Bratislava region, intra-regional cooperation was higher than cross-regional cooperation. For teams located within the Žilina and Košice regions, cross-regional cooperation was significantly higher.

Table 1. Basic network parameters
(Source: Calculations in Gephi based on the data from a questionnaire survey)

NODES	32
EDGES	91
DENSITY	0,092
AVERAGE DEGREE	2,8

Table 2. Geographical localisation of research network actors of public R&D organisations in the field of Industry 4.0

	Bratislava	Trnava	Žilina	Košice	Prešov	Total
Number of	13	2	8	8	1	32

teams						
Number of researchers within these teams	271	114	130	143	23	681
Intraregional cooperation (no. of coop.)	28	1	1	5		
Cross-regional cooperation (no. of coop.)	21	7	10	18	1	

The prevailing cross-regional cooperation suggests that geographical distance is not a key parameter in choosing a cooperation partner. Cross-regional cooperation was relatively high between teams in Bratislava and Košice situated at opposite ends of the Slovak Republic.

Cooperation within individual organisations was also heterogeneous. Within the largest university, the Slovak University of Technology in Bratislava, cooperation between faculties and within faculties was relatively intensive. Within other universities, cooperation between its organisational units was relatively low. The Institute of the SAS cooperated with teams in Bratislava and Košice.

4.3. Centrality indicators

The weighted in-degree indicator indicates teams that were most often identified by other teams in the network as strategic, above-average quality partners. Among them were first- (except for one), second- and three third-level teams (weighted in-degree higher than three).

Values for the betweenness and closeness centrality indicators could be obtained for 14 and 17 teams, respectively. Other teams had 0 betweenness and closeness centrality, i.e. they were located on the edge of the network. The teams with the highest values of closeness and betweenness centrality were the first- and second-level teams, respectively.

The weighted in-degree indicator was correlated with the closeness centrality indicator to some extent, where Pearson's correlation coefficient was at the level of 0.56. The weighted in-degree and betweenness centrality indicators had a relatively strong dependence, where Pearson's correlation coefficient reached 0.77 (at workplaces where these indicators were non-zero). Figure 2 also illustrates this correlation.

The value of the weighted in-degree indicator is visualised by the size of the node, i.e. the larger the node, the higher its weighted in-degree centrality. The value of the betweenness centrality indicator is shown by the font colour; the darker the font colour, the higher the value of the betweenness centrality indicator reached by the team.

The colour of the font and the size of the node show that almost the same teams dominate. In other cases, the reason is either a low number of out-degree collaborations or entities that are already connected through others.
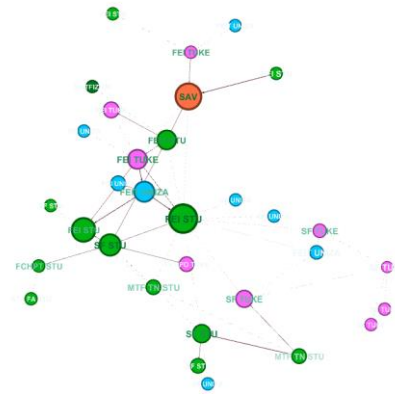

Figure 2. Industry 4.0 network and the position of network actors according to the weighted in-degree and betweenness centrality

The calculations of the values for the three key indicators mentioned were the basis for determining the key teams of the network. Key teams were identified as those with a higher than median weighted in-degree (values ranging 0–15, median 2), higher than median betweenness centrality (values ranging 10.16–284, median 28) and higher than median closeness centrality (values ranging 0.3–0.58, median 0.38). As a result, the five most important teams that met all three conditions simultaneously were identified as follows:

- Institute of Robotics and Cybernetics (STU BA) – first level
- Institute of Informatics (SAS) – first level
- Institute of Automation, Measurement and Applied Informatics (STU BA)
- Department of Cybernetics and Artificial Intelligence (TUKE) – first level
- Institute of Manufacturing Systems, Environmental Technology and Quality Management (STU BA)

These actors are important from various points of view because actors with a high closeness centrality within the network occupy a central position in this network. They are an important communication channel as they can approach all other actors in the network most easily, hence supporting the spillover effects. Actors with the highest betweenness centrality are important for network connectivity.

Identification of the key teams based on their values of centrality results in three out of the four teams identified in the first step as the first layer of the network.

5. Conclusion

The Industry 4.0 network represents a connected graph of cooperations between 32 domestic teams of public R&D organisations. Within the network, active actors with a high number of cooperation and those located in its network centre who can support knowledge transfer across the identified R&D network and thus have an important communication role are crucial. They represent significant entities that provide connections to peripheral network actors without direct access to the capacities and knowledge of the network centre. These workplaces ensure network interconnection and the possibility of further network expansion and improve information dissemination within the network. Identification of key actors based on the values of the network centrality indicators confirmed the results of Horizon data mining to a certain degree because three out of four actors were identified by both means.

The research network of public R&D organisations operating in the field of Industry 4.0 in the Slovak Republic is characterised by low density. Therefore, cooperation between R&D workplaces is insufficient. The relatively highest level of cooperation occurs between R&D teams located on opposite sides of Slovakia, i.e. between Bratislava and Košice. Thus, geographical distance does not significantly limit cooperation. Most cooperations occur between universities; cooperation between faculties and within one faculty is less frequent. Intra-regional cooperation prevailed only in the capital city. In other regions, cross-regional cooperation was dominant.

New connections are also important in addition to long-term partnerships between R&D teams. Collaboration of researchers with different backgrounds can positively influence productivity; these researchers can solve complex research problems effectively in areas where a strong disciplinary paradigm is still developing.

This study confirmed that several variables are important to creating new collaborations and thus not limited to geographical proximity, institutional affinity and size of the workplace. Cooperation has various motives. The analysis of the Industry 4.0 research network in Slovakia and many scientific studies suggest that the choice of a strategic research partner based on numerous factors is often subjective and individual.

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