Journal of Knowledge Management

How to measure trust: the percolation model applied to intra-organisational knowledge sharing networks

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Abstract

Purpose – *The present paper aims to explore how to measure trust as a receptivity force in an intra-organisational knowledge-sharing network with the help of self-developed algorithms of modelling percolations.*

Design/methodology/approach – *In this paper, a completely new methodology is applied by using a sample study of an international company's financial centre as an example. Computer software has been developed to simulate the network and calculate the percolation thresholds by combining its characteristics, thereby revealing what and to what extent connectivity and trust, respectively, influence knowledge sharing.*

Findings – *The application of computer modelling to build up a percolation network is useful for answering questions about the determinants of knowledge sharing. Arguably, the authors demonstrate how the applied new methodology is superior in addressing how to measure the critical values of trust, connectivity and interaction issues, as well as leading to better insights about how these can be managed. The present paper confirms that trust is an essential factor influencing knowledge sharing and that there is a reciprocal effect between social interaction and trust.*

Practical implications – *The model provides a useful tool for assessing features of the intra-organisational knowledge-sharing network and thus an important foundation for implementing actions in practice. The findings of this study imply that managers should consider the important role of task-related trust between actors and in general for knowledge sharing. With the help of percolation modelling, the degree of trust in an organisation can be computed, and this provides managers with an approach for managing trust.*

Originality/value – *The topic of "how can trust be measured" is very important and is becoming even more important now because the financial crisis and other issues are raising questions about trust and moral compass rather than financial data. A percolation-based approach to studying knowledge sharing has not been researched in depth before now, and this study attempts to fill that gap. Fundamentally, this multidisciplinary research adds value to the theoretical foundation of the percolation network and research methodology to be used in social sciences and gives an example of their potential practical implications.*

Keywords *Empirical research, Knowledge management, Knowledge sharing, Organisation, Percolation*

Paper type *Research paper*

Received 15 November 2015
Revised 22 March 2016
3 July 2016
13 July 2016
Accepted 16 July 2016

The authors would like to acknowledge the constructive comments and encouragement of Professor Carla Millar, the Editor of the Special Issue of *JKM* and anonymous reviewers.

1. Introduction

A change from industrial economy towards a so-called knowledge economy has taken place and has resulted in a shift in key resources. In the knowledge economy, intangible assets, or intellectual property, are assumed to be the key resources of competitive advantage. Whereas in the industrial era most companies necessarily had to possess a location and a production plant, in the knowledge economy, competitive advantage can exist anywhere where someone has the willingness and capability to mobilise brainpower (Knapp, 1997). Organisations believe that knowledge is a key resource for innovation and competitive advantage and are ready to invest a lot of money into knowledge management (KM) software. However, until now, such activities have often failed in practice (Block, "In such a fast changing world, cooperation and tacit knowledge have become strategically important, especially for knowledge-intensive organisations."

2013). Some researchers acknowledge that the reason for this is that they focus mainly on technology-based solutions (Abrams *et al.*, 2003; Call, 2005). Others refer to investment behaviour, which shows a somewhat careful approach to investing in R&D, space for creativity and a benevolent working atmosphere (HWWI, 2009; Ebeling *et al.*, 2012).

These reasons underpin the recent paradoxical situation: since the nineteenth century, the economy has been running based on the idea of *homo oeconomicus*, i.e. competition instead of cooperation, rationality in place of emotions and individualism instead of collectivism. However, in the twenty-first century, with the help of information and communucations technologies (ICT), individuals and the world at large have become interconnected and are calling for cooperation. The internet, in particular, brings people and knowledge together globally: the latest data about internet users worldwide, collected in June 2015, shows that almost half of the world population is using the internet, whereas in 2000 this figure was only 5 per cent (Miniwatts Marketing Group, 2015). With the help of the internet, individuals can globally communicate, share and interact. Moreover, there are economic success stories of internet-based innovators, such as knowledge-intensive organisations (KIO), for example, Google, and social media, such as Facebook. In the global and digital world, people, especially the young generation, learn to adapt to the fast pace of change, complexity and uncertainty in life. Furthermore, people are forced to take responsibility for their own lives, whereas predictable models of living and hierarchical structures are dissolving. The phenomenon of global connectivity, with its access to knowledge and knowledge-sharing possibilities worldwide, is very present. In such a fast changing world, cooperation and tacit knowledge have become strategically important, especially for KIO.

Conversely, it is rather difficult or even impossible to build any relationship and cooperation without trust. So, trust plays an important role and seems to be increasingly important for the sustainability of organisations in times of financial crisis and global disruptions. Despite the fact that intangibles such as trust have become so important, the ongoing challenge for both academics and practitioners remains how to measure these. In this paper, the topic of "how to measure trust" is taken up and a new methodology is applied to analyse this. In more detail, the interconnections between trust, knowledge and people are studied by referring to the percolation theory as our methodological basis. This is a unique approach deriving from physics and a superior way of analysing trust in intra-organisational knowledge-sharing networks. A new computer software has been developed to model a percolation network to develop an approach to managing trust within an organisation. As an example, our percolation model is applied to a case study based on real empirical data of a knowledge-sharing network underpinned by the research question:

RQ1. To what extent is successful knowledge sharing likely to take place within the network, and how can it be encouraged or regulated by trust?

2. The relationship between knowledge-sharing network and trust

In the neo-technological view, described by Antonelli (1996), "the generation of new knowledge is the result of the interaction of non-institutionalised efforts of innovators, which are based on the processes of learning and existing skills specific to every actor". In other words, knowledge generation and innovation creation require various kinds of highly individualised knowledge. In this context, the process of knowledge sharing between involved actors becomes a crucial element.

In this article, the focus of research is on the interaction between employees within organisations, particularly within knowledge-sharing networks. This research considers knowledge-sharing networks as a subsystem of organisations in which the foundation is employees as the holders of knowledge. While knowledge is held individually or within groups, the process of knowledge sharing reflects an iterative process of social interaction between at least two actors in which knowledge is shared with the help of communication and ICT (Nonaka and Takeuchi, 2004; Block, 2013). Indeed, the field of social interaction can focus on different aspects, but the focus of the present study is work-related intra-organisational knowledge. Interrelations between employees are described by social interaction ties building up a social network that has been characterised by Bourdieu (1986) as "an aggregation of individual and collective – conscious or unconscious – investments with expected outcomes being both short and long term [. . .]". In this study, the social network is narrowed down to a knowledge-sharing network.

2.1 Characteristics of a knowledge-sharing network

Knowledge-sharing interactions and relationships are affected by their environments and the contexts in which they take place. First, relationships are influenced by the behavioural positioning of each actor in view of a cooperative mode to innovate (instead of learning and conducting their tasks alone). This will indicate the willingness and ability of actors to participate, interact and share knowledge, a crucial condition for knowledge sharing to take place. Second, knowledge sharing as a type of cooperative behaviour demands a reasonable level of common understanding of work tasks and of the vision of the organisation. For example, Tsai and Ghoshal (1998) acknowledge that employees are more likely to reach organisational goals when they share a vision and values. Evans (2013) points out that trust and shared vision have the greatest effect on willingness to share and use knowledge. Third, the social structures and roles of participating actors are important. In this context, differences in power and social status may impact social structures. On the one hand, there are formal knowledge paths provided by the organisational chart. On the other hand, informal paths are elaborated by certain people and groups within the network (Block, 2013). These paths build up both strong and weak ties among actors. A dense network consisting of strong ties reflects an optimal opportunity to access valuable resources such as knowledge, according to Bourdieu (1986). On the other hand, Granovetter (1973) was one of the first researchers who demonstrated the importance of weak ties as well. With regard to the structure of knowledge-sharing networks, questions arise which pertain to how dense or open the network should be in terms of completed knowledge sharing or how many agents need to be connected in a network or between sub-networks for successful knowledge sharing to take place. Finally, social interactions and knowledge sharing are joint actions characterised by reciprocity. In other words, all participating parties should perceive the sharing process to be beneficial in the long run, otherwise it is unlikely to be repeated. The underpinning concept is trust. In management literature, there is a common agreement that trust is a means to reduce complexity of information, is an essential part of people's decision-making processes and acts as a bond between people. Numerous empirical studies demonstrate interdependence between trust and knowledge sharing (Werner *et al.*, 2016; Levin and Cross, 2004; Mayer *et al.*, 1995;

"Conversely, it is rather difficult or even impossible to build any relationship and cooperation without trust."

"In general, the 'connectivity' and 'receptivity' of nodes are considered to be the two main forces pushing percolation processes forward."

Evans, 2013). For example, Field (2003) points out that trusting each other is necessary to be able to truly believe in gaining (future) benefits from the relationship. Trust is assumed to be a critical enabler for social interactions and for knowledge sharing. It moreover means that the knowledge-sharing process is inherently risky as otherwise there would be no need for trust.

In this study, knowledge sharing is considered to be a circular process conditioned by the existence of a certain level of trust.

2.2 The concept of trust and knowledge sharing

Trust is a phenomenon with multi-layered definitions in different scientific fields, yet fundamentally, a consensus about what trust actually means has not yet been reached. In this paper, trust is looked at within an organisational context and specifically the concept of trust as being interlinked with intra-organisational knowledge sharing.

The concept of trust is closely related to social capital and the relational dimension therein. Accordingly, cooperation or social interactions could not exist and develop without a reasonable level of trust. Furthermore, Nahapiet and Ghoshal (1998) argue that there exists a two-way interaction between trust and cooperation, observing that "trust lubricates cooperation, and cooperation itself breeds trust", which in turn may facilitate the sharing of knowledge. In terms of organisations and markets where situations imply a certain level of uncertainty, employees, managers and customers will be unlikely to merely believe their colleagues, managers and producers but will rather need to assess the trustworthiness of the trustee and the truster's general propensity to trust others (Mayer *et al.*, 1995). So, in a work-related context, the second perspective has become more accepted. In KM literature, an often-cited definition of trust is given by Mayer *et al.* (1995) and refers to the latter trust perspective: trust is "the willingness of a party to be vulnerable to the actions of another party based on the expectations that the other will perform a particular action which is important to the truster, irrespective of the ability to monitor or control that other party". This and other definitions show that expectations and vulnerability are essential elements of trust.

Intra-organisational trust can be further conceptualised into numerous types. With regard to the purpose of this research, we consider personal versus depersonalised trust and horizontal versus vertical trust (Block, 2013). Personal trust is a generalised expectation that the other will act according to how he/she presents him/herself. It is based on person-to-person interactions and thus plays an important role in intra-organisational knowledge sharing, including belief in reliability and competency. On the other hand, depersonalised trust refers to the trust placed in the system, i.e. how employees trust managers who work out rules and internal mechanisms, along with the mechanisms themselves. Furthermore, trust can be differentiated as horizontal and vertical trust. While the latter type regards the trust relationship between subordinate and supervisor, horizontal trust refers to co-worker trust, i.e. trust between employees within and across their teams.

Both personal trust and horizontal trust are necessary conditions for tacit knowledge sharing. Nevertheless, vertical trust and system trust reflect frame conditions which may either hinder or foster knowledge sharing significantly within organisations. Basically, what people experience affects future expectations and activities. Similar to trust, the decision to participate in knowledge sharing is based on personal perception or rather expectations of outcomes. If the knowledge sharing process is perceived as positive, the process is likely to continue and vice versa. If knowledge sharing is frequently repeated, a positive attitude towards knowledge sharing will be internalised (Block, 2013).

In the present study, the knowledge-sharing network relating to the impact of trust is built upon an empirical case study examined through data from 97 specialists working for the financial services within a global company. The methodology used herein is percolation theory and the theoretical background, as well as the modelling process, are explained in the following chapter.

3. Percolation modelling applied to knowledge-sharing networks

In this research, trust and its interaction in a network of knowledge sharing within an organisation is built upon the theory of percolation processes. As far as the focus of our study is related to social interactions and trust, the social percolation model is referred to, in which social actors and connections within an organisation are the focus. The present research aims to model percolation algorithms for intra-organisational knowledge sharing, wherein the critical point of trust can be measured.

The roots of percolation theory trace back to Physics and Chemistry, pioneered by Broadbent and Hammersley (1957), and it has been developed for researching clustered and non-clustered environments, networks and diffusion processes (Tarasevich, 2002; Zhukov and Aleshkin, 2008). From a mathematical point of view, percolations are part of probability theory in networks.

The basic notion of percolation theory can be described as follows: let us imagine a square net and suggest that every square (or cell) of this net can be either "occupied" or "free". Occupied cells are either isolated from each other or grouped together with their closest neighbouring cells: these groups are called clusters. If the probability p of becoming occupied is high, there will be many occupied cells united within a cluster. If the cluster connects two nodes of the net, percolation occurs and the cluster is called "connecting" or percolation cluster. In our case, the network in question is a knowledge-sharing net consisting of nodes (actors) which can be either "occupied" or "free".

Percolation theory may be used in solving a wide variety of problems, for example, in researching the reliability of computer networks, termination time of an epidemic and forest fires and in modelling transitions of the brain. Beyond, there are examples with respect to social sciences, for instance, Cont and Bouchaud (2000) research the influence of random communication structure on financial market fluctuations. In Zeppini *et al.*'s (2013) work, a diffusion model for an innovative product within a market comprising a structure of social relationships is implemented, and information diffusion is described using the percolation approach. Bolourian *et al.* (2009) study the behaviour of people in social networks and the dynamics of information diffusion in the Blogosphere which can help social networking sites to capitalize on their audience. There are also a few examples of percolation-based research into knowledge sharing and knowledge networks (Grebel, 2005; Navaretti *et al.*, 2013; Popescul, 2012). However, in these articles, the theory of percolation as such is not applied, only the concept of percolation is used to mean "connectedness". For example, in

"Managers and leaders should recognise trust as a leverage and develop an environment and atmosphere wherein trust among people can grow – in order to share and create knowledge in a knowledge-intensive organisation."

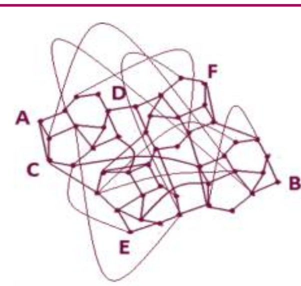
the works by Zhou (2016) or Morone *et al.* (2016), algorithms of graph search are discussed, but percolation thresholds, i.e. critical points at which percolation occurs, are not calculated. In Chen *et al.* (2007), the critical points at which percolation occurs are investigated, but such features of a network as the number of bonds per node (or number of connections per person) are not considered.

It has been seen that percolation theory has common axes, with the aims of this research being to study intra-organisational knowledge sharing. The intensiveness of knowledge sharing and trust could be described within the framework of percolation theory because this is a general theory for researching any networks and their diffusion processes. Beyond this, in our research, percolation shall be applied with the aim of filling the current research gap, i.e. thresholds shall be calculated depending on the average number of bonds per node, both tasks of bonds and nodes shall be resolved. So, percolation theory is arguably a promising avenue for future research and could become a useful instrument to gain a better understanding of self-organisation and the creation of new structures within an organisation (Tarasevich, 2012), as well as for studying influential factors such as trust and other factors of connectivity and receptivity.

3.1 Features of social percolation model for knowledge sharing

First of all, in this research, we refer to a social percolation model, i.e. social actors and connections within an organisation. This kind of network is more diverse – actors have varying degrees of knowledge, trust, ability to share, etc. Conversely, in physics, researchers will tend to deal with more or less homogenous material and often investigate regular networks (rectangular or square) (Solomon *et al.*, 2000). However, networks of people cannot have a regular structure – the structure is random – as in Figure 1. In more detail, this means diffusion of various types of knowledge can happen along various paths, many of which exist simultaneously. Each connection between two connected nodes can be open for knowledge sharing with probability *p; p* can represent the probability of openness of the node or usefulness of the knowledge or the combined effect of both, etc. So, an analytical solution for any problem is difficult to ascertain, and only computer modelling can help with this. Another problem in percolation-based studies of knowledge transfer within a social network is that where the system undergoes its critical point and percolation happens is not likely to be known in advance. In the present case study, the issue of trust is central; so, the critical point can be used for protecting the functionality of the network by maintaining a policy of selecting employees with an “intrinsic propensity towards openness” and trust (Navaretti *et al.*, 2013). With regard to both challenges, in the present research, percolation algorithms are modelled for intra-organisational knowledge sharing, wherein the critical point of trust can be defined.

Figure 1 The structure of the social network among a company’s employees A, B, C, D, E



Source: Zhukov and Lesko, 2015

In more detail, this means diffusion of various types of knowledge can happen along various paths, many of which exist simultaneously. Key sources in the knowledge sharing process are the knowledge sender and knowledge receiver who encourage and determine whether percolation occurs. It is assumed that each connection between two connected nodes can be open for knowledge sharing with certain probability (p); p can represent the probability of openness of the node or usefulness of the knowledge or the combined effect of both, etc. As far as we are interested in the interaction process between the actors, p is attached to each bond (connection) between two neighbouring nodes (actors), in contrast with the node (site) model, wherein every node exists with certain probability (Bolourian *et al.*, 2009; Tarasevich, 2002). Furthermore, in physics, it is assumed that percolation results from the counteraction of two forces – connectivity and receptivity. This means that the percolation probability (PP) is defined as an equation PP = (pf,pt) with the predictor variables probability of receptivity (pf) and the probability of connectivity (pt). Receptivity and connectivity are not perfectly symmetrical in their influence on PP, i.e. receptivity of the system is more fragile than its connectivity: $pf\,(p) < pt\,(p)$ whenever $0 < p < 1$ (Antonelli, 1996; David and Foray, 1996; Hammersley and Welsh, 1980). Therefore, percolation is easier when connections are imperfect but receptivity is good rather than when connections are perfect but receptivity is weak. However, this does not mean connections should be weakened, whereas receptivity based on trust should be increasingly fostered but rather that the right balance must be kept. In the present case study, connectivity reflects the number of connections between the actors in the network, whereas receptivity is defined by the value of knowledge and work-related trust.

Furthermore, in this study, percolation algorithms are modelled to find out the critical point at which percolation (knowledge sharing) is more likely to happen. In the present case study, the critical point refers to both connectedness and receptivity (trust). On the other hand, the critical point, or rather "percolation threshold", of connectedness refers to the percolation environment which is represented by a network of people and departments in an organisation (Figure 1). Here, the guiding question is how many actors should participate in the process of knowledge sharing to make percolation possible? This means that the percolation threshold is a critical proportion (minimal number) of nodes in the network which can provide percolation from point A to point B; in other words, it is a critical proportion (minimal number) of employees which can transfer knowledge from A to B. While it is manageable to analyse various possible paths by hand in a small network, computer modelling becomes necessary when the number of actors in the network is large.

3.2 Assumptions

The proposed percolation model applied to knowledge-sharing network is based on the following four assumptions:

- *Assumption 1*: It is assumed that not all knowledge is publicly available, so people need to look for the knowledge they lack.
- *Assumption 2*: In this model, people are the nodes in a network of social relationships within an organisation, and their ability to share and to absorb knowledge are heterogeneous, expressed in probabilities of connectivity and receptivity.
- *Assumption 3*: A person will share knowledge only if two conditions are met: first, if there is motivation to share and trust, and secondly, if the knowledge sharing channel is open.
- *Assumption 4*: The greater the trust, the more likely percolation is to occur. Decreasing the level of trust is like removing bonds from the network. Employees with low or no trust will cease to share knowledge.

Finally, this model considers both static tasks dealing with self-organised percolation transition and the dynamic task which is approached by slightly enhancing our experiment: the data on trust is modified as if people learn how to trust during the process of knowledge sharing. In static tasks, the probability p is stable at every step of knowledge sharing. In dynamic tasks, p changes at every step as the condition of every node changes, for example, as a result of learning. Dynamic tasks are more complicated because certain rules should be fixed to define how the condition of certain nodes will change depending on the volume of knowledge the node received at the previous stage.

4. Data collection and simulation algorithms

Rephrased in terms of the concepts of percolation theory described above, the objective is to research the probability that knowledge sharing will occur depending on the network structure which depends on the trust one agent has in the other actors with whom they must work. More precisely, with the help of specially developed computer modelling software, the percolation threshold for a network is calculated where bonds have certain features of connectivity and receptivity which are defined by value of knowledge, degree of connectedness and work-related trust. This percolation modelling software is applied to the present case study.

4.1 Data collection

The empirical data were collected from an in-house centre for financial expertise which was established to provide the best customised service in a multinational company located in Northern Europe. The desire of employees and departments to interact and share their knowledge in such financial knowledge intensive services is a key success factor to reach the best performance; 97 specialists of the financial centre participated in the study. In total, 59 responses were received (equivalent to a 61 per cent response rate). The relevant questions from the questionnaire are placed in the Appendix. All data are grouped into square symmetric matrices of 59 by 59 elements with the values of p_{ij}, i,j = 1 [. . .] 59. There are three matrices characterising connectivity:

1. The *Connectivity Matrix* consists of answers employees gave to the question "With whom do you interact"? (Please, see the Appendix) This is a binary matrix, 59 × 59: if there is an interaction, "1" is placed into the cell $pt_{ij} = 1$, otherwise $pt_{ij} = 0$.
2. The *Knowledge Flow Matrix* (also 59 × 59) represents the strength of connections between people. The question asked of employees was "How often do other employees share knowledge/information with you"? A Likert scale, ranging from 1 = not at all to 5 = very much was numerically transformed using Harrington's (1965) desirability function: $pt = 0.1$ for "never", 0.3 for "rarely", 0.5 for "sometimes", 0.7 for "often" and 0.9 for "very often". The values of pt are placed into the corresponding cell for every pair of individuals. For example, if employee "i" is asked "how often employee 'j' shares knowledge with you" and he/she answers "often", then the value of 0.9 if put into cell ij, $pt_{ij} = 0.9$ in this case.
3. The *Usefulness Matrix* represents employees' (59 × 59) answers to the question "Please assess the usefulness of information transferred to you by your colleagues" scaled 0.1-0.9 in a similar way to the *Knowledge Flow Matrix.*

Furthermore, the matrices are combined, so that every score of connectivity is multiplied by a weight taken from the *Knowledge Flow Matrix*, from the *Usefulness Matrix* or from both.

There are three matrices characterising receptivity with probabilities pf scaled in a similar way, when the Likert scale with scales ranging from 1 = not at all to 5 = very much was numerically transformed in a similar way to the Knowledge Flow Matrix. The values of pf_{ij} are placed into the corresponding cell for every pair of individuals i and j.

- *Real Trust Matrix*: Contains the people's answers for "Please indicate the extent to which you perceive the other teams as trustworthy, insofar as you are in task-related contact with them".
- *Fulfilling Promises Matrix* consists of the answers for "In general, do you think that people from other teams always keep the promises they make to your team"?

- *Reliability Matrix*: Employees responded to the question: "In general, can you rely on the quality of knowledge you receive from the other teams"?

As pointed out earlier, applying percolation theory requires a large data set. This is quite challenging to achieve in real world settings. However, in this research, the solution is found in the form of simulations run by the developed algorithms based on the data of the case study.

4.2 Computational modelling of knowledge-sharing network based on trust

Special software has been developed to conduct social percolation modelling of knowledge-sharing network based on empirical data (software patented by Zhukov and Lesko). For the majority of computations, cloud computing Windows Azure technology was used. The input variables for the programme are the type of task needed to solve, number of nodes and bonds, modelling precision and strategies for blocking the nodes.

The experiments modelling knowledge-sharing network were conducted in two stages:

1. building percolation simulation algorithm and calculating the percolation threshold for the empirical data; and
2. modelling dependence of the percolation threshold and the average number of connections (bonds) per actor (node).

4.2.1 Building percolation simulation algorithm and calculating percolation threshold based on the survey results. With the help of experimental computing, the value of the percolation threshold (ξ) can be determined. For this purpose, we selected a pair of random nodes o_i and o_j with a statistically large number of experiments N_i defining how many times m_i there is a free pathway between these nodes o_i and o_j in each set of experiments i in the researched network. In doing so, the value of percolation threshold can be calculated in dividing the frequency by the number of experiments ($\xi_i = m_i/N_i$). The same procedure is repeated for other pairs of nodes. After conducting all sets of experiments (M), the percolation threshold of the whole network (ξ) is calculated which reflects the average over all single thresholds:

$$\xi = \frac{1}{M}\sum_{i=1}^{M}\xi_i$$

The results of modelling the percolation threshold (ξ) for Usefulness Matrix combined with Connectivity Matrix are presented in Table I.

It is worth mentioning that percolation threshold is an integrative characteristic of the whole structure, not only of its specific connections. ξ shows how the network will function as a whole, the degree of its general efficiency no matter whether some connections function better or worse.

Table I Percolation thresholds ξ for various combinations of connectivity and receptivity characteristics

No.	*Combination of matrices* *I*	*Percolation thresholds ξ receptivity "as is"* *II*	*Percolation thresholds ξ after increasing receptivity (trust) by 50 %* *III*	*Percolation thresholds ξ when trust is perfect by 100 %* *IV*
1	Connectivity + Knowledge Flow	0.263	0.311	0.334
2	Connectivity + Usefulness	0.295	0.344	0.390
3	Connectivity + Knowledge Flow + Usefulness	0.186	0.215	0.264
4	Connectivity + Real Trust	0.296	0.348	0.416
5	Connectivity + Fulfilling Promises	0.316	0.372	0.430
6	Connectivity + Reliability	0.294	0.363	0.419
7	Connectivity + Real Trust + Fulfilling Promises	0.262	0.307	0.344
8	Connectivity + Real Trust + Fulfilling Promises + Reliability	0.271	0.324	0.377

4.2.2 Modelling dependence of the percolation threshold and the average number of bonds per node. In the next step of the research, an approach is proposed to solve the task of how the percolation threshold (ξ) in a random network with numerous paths depends on the average number of bonds (connections) per node (actor). In the present study, the *Connectivity Matrix* defines bonds among employees. If a connection between nodes *i* and *j* exists, 1 is entered, and, if there is no connection between two nodes, 0 is entered. Furthermore, the *Connectivity Matrix* is multiplied by the *Knowledge Flow Matrix*, the *Usefulness Matrix* and the *Real Trust Matrix* (each matrix contains values from 0.1 to 0.9). As a result, there is a network wherein each bond has a weight which is defined as "trust probability" σ_j for connection *j*.

For a large network with at least 100 nodes and several thousand bonds, it is possible to consider average characteristics such as average value of trust probability $\overline{\sigma} = \frac{1}{K}\Sigma_{j=1}^{K}\sigma_i$ and average number of bonds per employee $\overline{\phi} = \frac{1}{K}\Sigma_{j=1}^{K}\phi_i$ where K is the total number of connections among employees.

- Modelling the situation when the knowledge transmission in the percolation network is blocked

At this stage, the scenario has been expanded from defining percolation thresholds for bonds between pairs of nodes towards networks with various numbers of bonds per node. The aim is to find dependence between the average value of probability that it is impossible to transmit knowledge between two randomly chosen nodes of a random network, which has numerous paths between nodes (Figure 1) and a various average number of bonds per node, and average probability of breaking a bond are represented in Figure 2.

As shown in Figure 2, the linear parts in the middle of curves 1-6 can be identified and extrapolated until they cross the horizontal axis at points which can be accepted as lowest values of percolation threshold in the corresponding network.

- Relationship between percolation threshold and number of bonds per node

Figure 3 represents the dependence of the lowest percolation threshold from the average number of bonds per node acquired according to the approach described above: as the number of bonds increases, the percolation threshold steadily grows.

Figure 2 Modelling percolation network blocking for various average number of nodes for the task of bonds

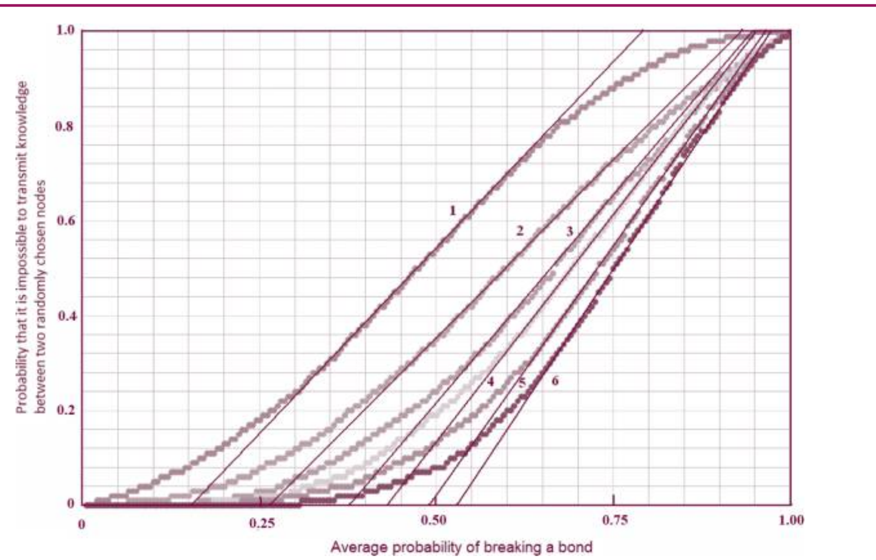
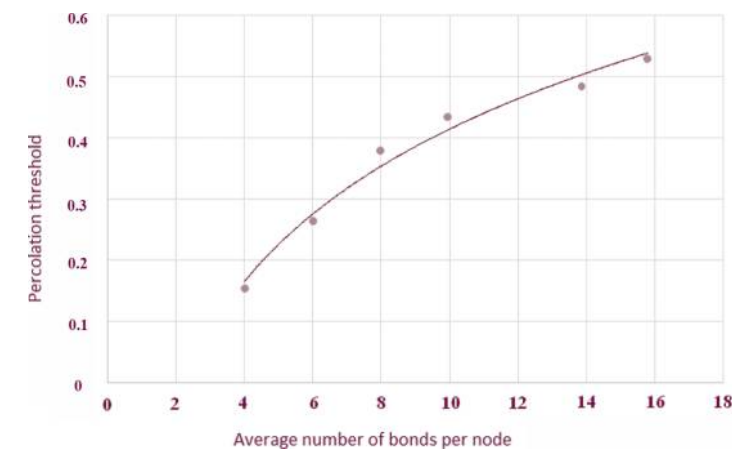


Figure 3 Dependence of the percolation threshold in a random network and the average number of bonds per node



The data in Figure 3 can be linearised in coordinates: lnP(x) depending on $z = 1/x$ [natural logarithm of percolation threshold P(x) depending on an inverse value to the average number of connections x per node]. The dots in Figure 4 represent experimental data, whereas the solid line corresponds to a linear model of dependence: $y = -6.581z - 0.203$, with large correlation coefficient $r_{yz} = 0.992$ (significant at $\alpha = 0.01$ level).

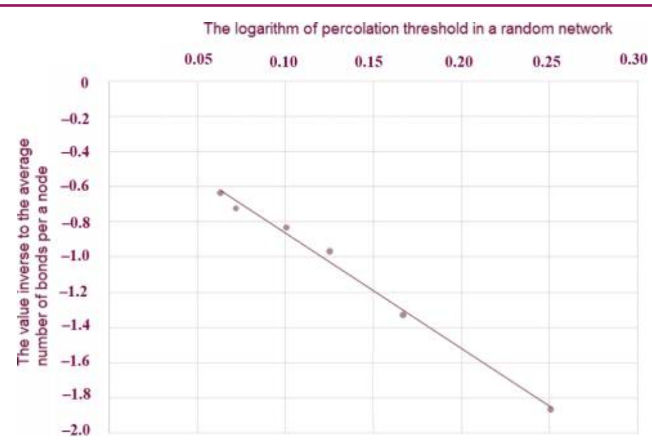
When $z = 1/x = 0$ (which is the case when $x = \infty$), we get: $y = \ln P_0 = -0.203$, and the size of percolation threshold, when the number of bonds per node is infinitely large, equals $e^{-0.203} = 0.815$. So, the network will work (employees will share knowledge) until the probability of breakdown of bonds reaches 0.815.

5. Discussion

5.1 Research results

First of all, this paper represents an attempt to contribute to the topic of how to measure trust within a knowledge-sharing network. This study proposes a percolation model that can be used in researching the role of trust and connectivity in intra-organisational knowledge sharing. This is quite a new interdisciplinary approach, which combines the notion of trust,

Figure 4 Dependence of the logarithm of percolation threshold in a random network on the value inverse to the average number of bonds per node



methodology of researching percolation originating from Physics and computer modelling. It is demonstrated herein that the methodology of percolation is a potentially useful way of analysing the structural topology of networks in addition, for example, to Social Network Analysis (SNA). In SNA the connectivity matrix is also built, with the key concepts being density, centrality, distance, clusterisation, etc. However, percolation threshold for the whole network and its dependence on the average number of connections per node are not considered. This is exactly the novelty of our research: in the new approach discussed here, distance or centrality are not spoken of, but the network is considered as a whole; its features are described using the percolation threshold. The reasoning behind this is that the information generated by any network nodes, no matter whether they have many connections or only a few, if they are central or not, can be useful and valuable for the company. Percolation threshold is a general characteristic of a network; it can be high for one type of information and low for another, i.e. the network can operate as a filter showing which type of information spreads faster.

Second, this study supports findings in the KM field of research, which argue that trust is an essential factor impacting knowledge sharing and that there is a reciprocal effect between social interaction and trust. In this article, the intra-organisational knowledge interaction network is investigated. In general, the "connectivity" and "receptivity" of nodes are considered to be the two main forces pushing percolation processes forward. In this article, the former reflects the number of communications between actors in the network, whereas the latter describes the actors' ability to absorb knowledge based on task-related trust.

Third, this research has developed a percolation simulation algorithm for the knowledge-sharing network. Several types of experiments were conducted and reveal interesting findings: M = 1000, $m_i = 1000$, which means 1,000,000 experiments for each combination of Matrices (Table I, column I). The percolation thresholds for connectivity and receptivity "as is", i.e. as was revealed in the survey, are shown in column II. In column III, there are percolation thresholds after the receptivity data were modified, i.e. as if people who did not trust, hypothetically learned to trust at the level of 50 per cent. In column IV, there are percolation thresholds after the people who did not trust earlier, "learned" to trust at the level of 100 per cent. With this the dynamic task of percolation was approached, i.e. we looked at how percolation threshold changes dynamically depending on the degree of trust among people.

When the *Connectivity Matrix* is combined with the *Usefulness Matrix*, the probability of percolation equals 0.295 and is highest in the first three combinations when receptivity/trust is not yet present. When putting *Connectivity, Usefulness* and *Knowledge Flow Matrices* together, we get the lowest percolation probability −0.186 – and it is clear that to increase percolation properties of the network, strength of connection, as well as usefulness of knowledge, should be fostered. At this stage, the probability that knowledge will find its way through the network is quite low.

After introducing weights of receptivity from the three trust matrices – *Real Trust, Fulfilling Promises, Reliability* (combinations 4-6) – it becomes evident that trust makes percolation probability higher. It has slightly more effect on percolation than, for example, knowledge flow and usefulness, which characterise connectivity. As a result of increasing trust, reliability and ability to fulfil promises, the force of "receptivity" increases which makes percolation threshold higher and allows the intra-organisational network to work better. This supports the theory developed by Hammersley and Welsh (1980), who state that it is more effective to increase receptivity of nodes (trust) than to increase connectivity.

Finally, columns III and IV show that percolation thresholds increase substantially as people gain trust, demonstrating the positive influence of trust on knowledge sharing. It is also visible from columns III and IV of Table I that by increasing trust by 50 per cent, the percolation threshold increases on average around 18 per cent, and, in case of 100 per cent trust, the percolation threshold increases by approximately 36 per cent. Compared to the development of communication paths and structural connections, trust is a stronger leverage. Besides the receptivity characteristics, it is the usefulness of knowledge shared which shows the strongest positive impact on successful knowledge sharing.

5.2 Implications

This study has several implications for managerial practices in enhancing knowledge sharing based on trust. First of all, it emphasises the role of trust as a receptivity force for knowledge sharing. As such, it suggests that managers and leaders should recognise trust as a leverage and develop an environment and atmosphere, wherein trust among people can grow – to share and create knowledge in KIO. On the other hand, attempts to develop communication paths and structural connections can be considered as an important infrastructure to contribute to the overall knowledge-sharing process. However, modelling performed with the new software once again proved the generalised asymmetry theorem of Hammersley and Welsh (1980) that receptivity of the system is more fragile than its connectivity: $pf(p) < pt(p)$ whenever $0 < p < 1$. So, percolation takes place more easily when connections are imperfect but receptivity is good. This means that it is important to foster openness and communicative behaviour among employees rather than make them connected through IT means. This approach would help the human resource management (HRM) department to expand the view in selecting the "right" leaders with appropriate skills for bringing knowledge sharing into life.

Second, knowledge sharing perspective implies a framework for knowledge-sharing culture which should be more receptivity-directed than connectivity-directed. As the results show, a certain level of trust is required to keep employees sharing their knowledge, but it is not desirable to invest all efforts into reaching a 100 per cent level of trust because the growth of trust will not lead to perfectly successful knowledge sharing. As far as the research is related to task-related trust, the aim should not be to reach a 100 per cent trust level because therein lies the danger of falling into a routine of blind trust (Block, 2012; Huotari and Iivonen, 2004), i.e. if everything is taken for granted and nothing is questioned, the risk is that processes may turn into pure information transfer rather than sharing of knowledge and nurturing disruptive innovations.

Third, the dynamic dependence of the percolation threshold on trust is demonstrated (Table I, columns III and IV). It was proven that when people learn to trust, the features of the system associated with transmitting knowledge improve (percolation threshold increases).

Fourth, another important result can be drawn from the above observations: even if the system is not perfectly connected, even if some nodes are randomly not "communicative", percolation will eventually take place and knowledge sharing will happen anyway; so if some members randomly violate certain "norms" of the organisation, this does not mean the process of knowledge sharing is necessarily broken. It is a hint for leadership – there is no need to make the norms too rigid and make people exchange messages or create databases all the time; it just destroys the desire in people to communicate and share ideas. Certain degrees of freedom in this case can only do good.

Lastly, this research has developed an approach for managing trust within the organisation. Our own computer algorithm is suggested to calculate the percolation thresholds within the network by combining various characteristics, thereby revealing what influences and underpins knowledge sharing. Modelling dependence of the percolation threshold and the average number of bonds per node provides an opportunity for the leadership to evaluate the need for action. Having conducted a sociological survey, it is possible to define the average observed value of the trust probability $\overline{\sigma} = \frac{\sum_{j=1}^{K} \sigma_j}{K}$ for the network and the average number of connections $\overline{\phi}$ per employee in the whole network. Moreover, by using $z = 1/\overline{\phi}$ and the equation $y = -6.581z - 0.203$ acquired for the task of bonds, it will be possible to define the critical value of $y = \ln \overline{\sigma}_{\text{crit}}$. If after sociological survey it turns out that the observed trust is $\overline{\sigma} \geq \overline{\sigma}_{\text{crit}}$, calculated according to the acquired equation, then the degree of trust in the company is good. Otherwise, it is important to either:

- increase the level of trust in the company. According to the calculations, the level of trust in the company should not be lower than 1 – 0.815 = 0.185 (as it was noted above, the percolation threshold equals 0.815, when the number of connections per node is infinitely large which means the network will perform its tasks until the probability of its blocking reaches 0.815); or
- increase the number of connections among employees. According to observed $y = \overline{\sigma}$, acquired after the sociological survey, and the equation $y = -6.581z - 0.203$, we define $z = 1/\overline{\phi}_{\text{crit}}$. If after the sociological survey we get $\overline{\phi} \leq \overline{\phi}_{\text{crit}}$, calculated by the acquired equation, then the average number of connections in the company is good. Otherwise, we would have to increase the average number of connections per person in the company.

In the present case study, the observed $\overline{\sigma} = 1.36$, $\overline{\phi} = 3.85$ gives us a percolation threshold of $\overline{\sigma}_{\text{crit}} = 0.15$. As $\overline{\sigma} > \overline{\sigma}_{\text{crit}}$, thus the degree of trust in the company is sufficient.

So, with the help of computer modelling, certain recommendations regarding the network topology can be formulated. The suggested approach helps to define the critical value of trust and average number of bonds per employee required to make the knowledge sharing system operate. In other words, percolation theory allows the development of an approach to manage the level of trust within the organisation.

5.3 Limitations

The findings of the present study are not free from limitations. Data were collected within one organisation only and thus generalisation is merely possible for a similar research object. Also, findings are based on self-reported data, which can be biased. In this case study, the percolation threshold rather concerns qualitative characteristics of processes in the system, i.e. relationships among employees within the organisation and trust. In spite of the fact that our research is based on a single case study, it is nevertheless a demonstration of applying the percolation theory. Another limitation is that the sample size is rather small. However, we have circumvented this challenge by conducting simulations based on gathered empirical data with the help of computer modelling. On the other hand, the method of using computer modelling software, which has been developed and applied for this case study, should be further assessed and verified in future research.

6. Conclusion and recommendations for further research

In this research, the focus lay in the interconnection between knowledge, people and trust, using the example of a knowledge intensive intra-organisational network. The principle point of interest was the application of the percolation theory related to the research questions: To what extent is successful knowledge sharing likely to take place within the network? And what are the critical values of average trust and average connectivity within the network? The current research showed that percolation theory is useful for answering the research questions.

So, let us summarise. First, with the help of percolation theory, features such as trust and structural connectivity in the knowledge-sharing network have been modelled. Second, it has been shown that there is a minimum level of communicative behaviour that a finite size knowledge network must maintain if knowledge is to percolate within it, so that knowledge sharing can occur within the network. This is a fundamental property of a percolation process. So, to make the network function, it is formally necessary to assess the average communication behaviour of the network members. One of the possible ways in which to do so was suggested in the present study. Third, it was demonstrated that knowledge sharing is strongly influenced by the connectivity features of the network and receptivity of the nodes expressed in particular in trust, perceived reliability of acquired knowledge, etc. The connectivity and receptivity features of the system shape the probability of knowledge percolation. Fourth, the study revealed important features of the knowledge-sharing process: its outcome can be predicted by modelling, i.e. for given measures of connectivity and receptivity. Fifth, it was demonstrated that if the system dynamically learns, i.e. if employees gain more trust as a result of team-building, bringing up a knowledge-sharing culture, then the features of the knowledge network improve – the knowledge percolation probability increases.

Finally, the features of percolation process also provide an insight into the fact that the system does not have to be "perfect", otherwise it becomes too rigid. The modelling showed that, whereas trust becomes stronger and stronger, i.e. employees learn to perfectly trust each other (a hypothetical situation), then the rate of growth of the percolation probability actually slows down (Table I).

This research is a starting point for using percolation theory for studying the influence of such factors as trust, quality and usefulness of knowledge and structure of the network on the process of knowledge sharing in an organisation, and, in doing so, it lays the foundation for further research. For example, more proof is required for the idea that to foster knowledge-sharing culture, it is more important to enhance trust within an organisation rather than merely build up connections, which is often costly and invariably many of these connections will later become redundant.

It is well known that the type of knowledge, implicit or tacit, influences the choice of the way in which, and speed at which, knowledge will be shared. It would be interesting to further investigate different types of knowledge and their effect on the percolation threshold.

An interesting hypothesis to test could be that the network can act as a filter for different information types. Let us imagine there are, for instance, four matrices with various information types: one matrix, as usual, contains connections (Matrix 1); another is a matrix of task-related trust, i.e. task to information connected with work (Matrix 2); a matrix of personal trust (Matrix 3); and a matrix of trust in administrative information (Matrix 4). If percolation thresholds are calculated for matrices 1 + 2, 1 + 3, 1 + 4, we will see that they are different for various types of matrices. If percolation threshold for "whispers", i.e. combination of Matrices 1 and 3 is higher than the one for "work", i.e. the combination of Matrices 1 and 2, this may mean that employees are more inclined to discuss personal problems than they are to do their jobs. So, in percolation modelling the network can be viewed as a filter system, which information spreads faster can be easily defined depending on its type. This hypothesis would be interesting for future investigation.

A hypothetical modelling exemplified in this research demonstrates how learning to trust and connectivity can influence the percolation threshold. According to percolation theory, there is a critical point signifying the start of the system's transition phase, which represents the start of active knowledge sharing. In this research, a learning curve is calculated, with trust increasing in relation to the process of knowledge sharing: from this, an approach to building a dynamic percolation model was developed. Furthermore, it would be interesting to develop a stochastic approach to all receptivity probabilities, modelling how employees learn to trust ore easily and to rely on each other more step by step. Such an approach may help to better understand and analyse how to manage the percentage of trust within such a knowledge network.

Finally, it would be very useful to reveal the paths of knowledge exchange, i.e. to undertake knowledge mapping which would help to find out where the knowledge goes, where it is blocked, its quantity and quality and the frequency of exchange. Furthermore, the visualised knowledge map could be compared with the real organisational structure and identify "the knowledge nodes", "the knowledge broker", etc.

To conclude, in this work, it was proven that the suggested approach is in many ways superior to other methods, such as, for example, the better known alternative SNA, because it considers the whole network features together in their complexity by calculating percolation threshold. This has never been done before. Using the example of one case study, it was shown how the method can be used to measure and manage trust within a company and how the network can act as a filter for various kinds of information. The novel approach discussed in this paper opens wide horizons for further research.

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Appendix

Relevant questions from the questionnaire:

Q1. "With whom do you interact"?

Q2. "How often do other employees share task-related knowledge/information with you"? Scales range from 1 = never to 5 = very frequently.

Q3. "Please assess the usefulness of knowledge/information transferred to you by your colleagues"? Scales ranging from 1 = less value to 5 = very value.

Q4. "How important is trust for you"? Scales ranging from 1 = "unimportant" to 5 = "essential".

Q5. "Please indicate the extent to which you perceive the other teams as trustworthy, insofar as you are in task-related contact with them". Five response options regarding each department: "less than 20 per cent", "more than 20 per cent but less than 40 per cent", "more than 40 per cent but less than 60 per cent", "more than 60 per cent but less than 80 per cent" and "more than 80 per cent".

Q6. "In general, do you think that people from other teams always keep the promises they make to your team"? Scales ranging from 1 = not at all to 5 = very much.

Q7. "In general, when you are under pressure at work, are you more or less likely to trust someone from another team"? Scales ranging from 1 = less likely to 5 = more likely.

Q8. "In general, do you trust the way work-related elements are being communicated between the different teams"? Scales ranging from 1 = not at all to 5 = very much.

Q9. "In general, can you rely on the quality of information/knowledge from the other teams you receive"? Scales ranging from 1 = not at all to 5 = very much.

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