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Knowledge Transfer in a Two-Mode Network Between Higher Education Teachers and Their Innovative Teaching Projects

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Abstract

Knowledge transfer (KT) and innovation diffusion are closely related to each other because it is knowledge regarding an innovation that gets adopted. Little research in learning analytics provides insight into KT processes in two-mode networks, especially in the context of educational innovations. It is unclear how such networks are structured and whether funding can create a network structure efficient for KT. We used a case-study approach to analyze a two-mode network of 208 university members (based on archival data) who worked together on 91 innovative teaching projects. Our results show that the two-mode network displays a decentralized structure and more clustering than can be assumed by chance, promoting KT and learning. To gain a deeper understanding of the kind of knowledge that is transferred in the network, we analyzed the effects of different educational innovation elements (e.g., game-based learning) as attributes of higher education teachers. Overall, our results suggest that funding and the creation of project structures in the context of educational innovation is a sustainable way to create KT, and therefore organizational change. Furthermore, the results imply that university practitioners need to implement networking interventions to create more connections between subgroups in teacher-related networks.

Notes for Practice

- This study empirically supports the theoretical framework of knowledge reservoirs that assumes knowledge is embedded in networks consisting of different modes.
- The transfer of complex knowledge (about educational innovations) can succeed in two-mode networks between higher education teachers and innovative teaching projects.
- Thus, educational reform programs should continue to support knowledge transfer regarding innovative teaching projects through funding, networking events, or training.

Keywords

Social network analysis, knowledge transfer, diffusion of innovation, educational innovation, higher education, two-mode network, small world

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1. Introduction

Learning analytics (LA) aims to gain insight into learning processes and learning environments using educational data about learners and their contexts by employing advanced data collection methods or advanced statistical tools (Ferguson et al., 2014; Leitner et al., 2017; Siemens & Baker, 2012). A central concern of LA in higher education (HE) is optimizing teaching behaviour, understanding education, and supporting strategic decision-making (Leitner et al., 2017). There is a strong connection to academic analytics (AA) since AA applies similar tools to LA to improve performance in educational institutions (Avella et al., 2016; Campbell et al., 2007). In the context of LA, learners or "data subjects" (Greller & Drachsler, 2012, p. 45) are often students in schools or HE institutions (e.g., Gasevic et al., 2017; Pauna, 2017; Rau, 2017). "Data clients" are individuals who benefit from the results of LA research and who can use LA research findings to initiate change processes. Such stakeholders can include (HE) teachers or administrators in schools and HE institutions (Greller & Drachsler, 2012). In LA studies, data clients and data subjects may be identical if, for example, LA provides (direct) feedback to students or HE teachers (Greller & Drachsler, 2012).

Research findings indicate that teachers play a crucial role in student performance and satisfaction (e.g., Glerum et al., 2021; Grohmann et al., 2021; Rienties et al., 2018). In LA research, teachers are only a "side product" to whom few studies are devoted, ignoring the potential and role of HE teachers in the educational learning environment (see Leitner et al., 2017, p. 12). Awareness and reflection are main goals in LA research (Greller & Drachsler, 2012; Scheffel et al., 2014). LA research findings on HE teachers could provide information that fosters HE teachers' awareness about their teaching. Other stakeholders, such as professional development staff, could develop specific interventions to increase HE teachers' instructional competencies or support organizational change. To focus on HE teachers in LA studies is important because they are the ones who innovate teaching at the course level and hence provide possibilities for better student learning and learning experiences.

Educational innovations are related to social innovations (Kolleck, 2014) and include, for example, "novel learning concepts" (Kolleck, 2014, p. 50). To evaluate the innovativeness of a learning concept, one can refer to the definition of innovation by Rogers (2003, p. 12), who describes innovation as an "idea, practice or project that is perceived as new by an individual or other unit of adoption." Therefore, changes are innovative if HE teachers use new (assessed by them, their students, and/or their colleagues) didactical and technical means (e.g., media, technology, and/or methods) in their courses, which they have not previously used (see Rogers, 2003). This definition implies that changes in teaching can only be evaluated relationally since the use of specific methods such as game-based learning or simulation methods might be well established in one teaching area but very new in another (Hauschildt & Salomo, 2004; Kauffeld et al., 2019).

The development and adoption of educational innovations is both time-consuming and expensive (e.g., Kauffeld & Othmer, 2019). To help HE institutions overcome these challenges, educational reform programs provide resources for educational innovations (e.g., Federal Ministry of Education and Learning, 2021; Kozma, 2005). Educational innovations are also supported by organizational funding and initiated by central departments of learning and teaching at HE institutions (e.g., Kauffeld et al., 2019) or by nonprofit organizations (e.g., Battelle for Kids, 2021). Regardless of funding, educational innovations depend on the motivation and interest of (HE) teachers to innovate and change their teaching and can be initiated by individuals (e.g., Hasanefendic et al., 2017). Related to these sources of educational innovations is their intended level of impact. Educational innovations may aim to innovate education at the program level (e.g., through the implementation of a national accreditation system), the system level (e.g., through a new strategic approach to curriculum design), and the course level (e.g., through the implementation of problem-based teaching in a course; Hasanefendic et al., 2017). These goals can overlap in practice. However, it is reasonable to assume that educational innovations initiated or adopted by individual HE teachers might be more likely to impact teaching at the course level.

The success of educational innovations in HE can, among other things, be assessed by their project- or system-oriented sustainability (Euler & Seufert, 2005). Project-oriented sustainability can be achieved by continuing and expanding individual teaching projects. Diffusion processes can lead to system-oriented sustainability of individual projects if they are diffused throughout the university system (Euler & Seufert, 2005; Stasewitsch & Kauffeld, 2021).

Limited resources, high turnover, and the prevalence of fixed-term contracts in HE institutions (Jütte et al., 2017; Kauffeld et al., 2018; Schomburg et al., 2012) call into question whether educational innovations, especially at the course level, are sustainable. It is unclear whether educational innovations can contribute to long-term organizational change, since it is partly unclear who will continue an innovation and how it will be transferred into different disciplines after the initiator has left the academic system. Therefore, the need for networks (e.g., Feixas et al., 2018) or communities of practice (CoPs; Mirriahi et al., 2012; Wenger et al., 2002) to diffuse educational innovations has been identified in the educational community. In CoPs, professionals (e.g., HE teachers) share knowledge, experiences, and best practices. They are characterized by a shared passion or goal (e.g., enhancing the quality of teaching through educational innovations). Through actively working together, they create new knowledge and practices. The idea is that in functioning CoPs, innovative HE teachers can help others with the use of new technologies or pedagogies, and learning can occur (Gehrke & Kezar, 2017; Mirriahi et al., 2012).

In practice, a functioning network where educational innovations are shared is often difficult to develop (Jütte et al., 2017). Network interactions and typologies are not determined a priori. They must be created using strategies and can be changed by network interventions (Centola, 2015; Portes, 1998; Valente, 2012). Hence, networks between HE teachers are often supported by additional funding and strategies like networking events or teacher conferences (e.g., Kauffeld et al., 2019). There is little research to provide insight into the structure of educational innovation networks and whether and how teacher network communities that enable educational innovation diffusion can be supported (Daly & Finnigan, 2010; Kezar, 2014). Hence, we aimed to answer the following research question in our study: Can innovation diffusion successfully occur in educational innovation networks?

2. Background

Educational institutions are complex adaptive systems made up of clusters and subsystems. In order to diffuse educational innovations efficiently, it is important to have a systemic approach and be aware of the role of different communities (e.g., departments) and stakeholders (e.g., HE teachers), as well as their interactions (Ferguson et al., 2014; Mirriahi et al., 2012). Adoption is preceded by acquiring knowledge about an innovation (Rogers, 2003). An (educational) innovation can consist of different components, such as an (educational) technology (e.g., eyetracking) and its utilization (e.g., pedagogical approaches like science-based learning; see, e.g., Appendix, Tables 5 and 6). The concept of reinvention indicates that innovations are usually not adopted in their entirety. HE teachers can learn about different components of an educational innovation and decide to reinvent, adopt, or discard them (Rice & Rogers, 1980). The implementation and reinvention of individual components might allow greater impact and system-wide diffusion of an educational innovation because HE teachers are freer to decide which components fit their needs or which approach their students might profit the most from. In organizations, learning transcends from the individual level, where one person transfers knowledge to another person, to a more global level, where many people in different settings transfer knowledge, such as groups (e.g., working on innovative teaching projects), departments, or organizational subunits (Argote & Ingram, 2000; Argote & Fahrenkopf, 2016). Through knowledge transfer (KT) in social networks, knowledge regarding educational innovations can be shared between HE teachers. Hence, KT in a social network can enhance collective learning and the diffusion of educational innovation (Kezar, 2014).

The knowledge reservoir framework suggests three primary sources of knowledge in an organization: tools (hardware and software, such as discussion forums), tasks (employees' tasks, especially their projects), and members of the organization (e.g., employees, such as HE teachers, interns, or students). Furthermore, knowledge is embedded in the combinations of these primary sources (Argote & Ingram, 2000; Argote & Fahrenkopf, 2016; Arrow et al., 2000; McGrath & Argote, 2001). Hence, KT can occur in different types of networks with different sources of information. The different sources of knowledge lead to different networks in which KT can occur, such as task-task networks, member-tool networks, tool-tool networks, or member-task networks (Argote & Ingram, 2000). Two-mode networks are member-tool or member-task networks because they consist of two types of sources, such as organizational members and tasks or projects that consist of different tasks (e.g., projects to develop or implement new, innovative teaching approaches). A member-member network is a one-mode network because there is only one type of knowledge source present in the network (e.g., members of the organization or HE teachers). Hence, individuals can transfer knowledge directly to each other or gain knowledge by using different sources (e.g., project reports, publications).

Usually, LA and social network studies focus on analyzing KT using one-mode network data between organizational members (e.g., Dado & Bodemer, 2017; Phelps et al., 2012). One-mode network data provides important information about KT between individuals (e.g., students or college faculty). However, one-mode network data can be subjective and is often collected through questionnaires or interviews (e.g., Froehlich et al., 2020). A primary goal of LA is to understand the interactions between learners, instructors, and instructional content (Avella et al., 2016). Connections between learners and instructional content represent two-mode network connections. Two-mode networks are rarely analyzed in LA research, and researchers need guidelines on how to analyze these networks (Dado & Bodemer, 2017). Moreover, the analysis of two-mode networks provides insight into the components of educational innovation (e.g., attributes such as game-based learning) and their diffusion in social networks. Hence, we aimed to answer our research question by analyzing KT processes in two-mode educational innovation networks using a case-study approach (Rowley, 2002).

2.1. The Empirical Case: A Two-Mode Educational Innovation Network in HE

In the context of educational innovations, it is important to investigate networks that combine tasks or tools and members (e.g., HE teachers), since educational innovations are often developed and implemented in project-based structures in HE institutions. Scholars often refer to such innovations, which aim at the course level of HE teaching, as "innovative teaching projects" (Benz-Gydat et al., 2021; Feixas et al., 2018; Jütte et al., 2017; Kauffeld & Othmer, 2019). We analyzed one specific educational innovation network to gain empirical insight into the efficiency of two-mode educational innovation networks for KT and learning. A single educational reform program supported this network. Such a case-study approach is appropriate if researchers want to answer the "how" and "why" questions of a phenomenon (Rowley, 2002): How are two-mode educational innovation networks structured? Why are they structured this way? Such an approach allows insight into the studied phenomenon, resulting in implications for research and practice.

In our empirical example, a mid-size German university (Technische Universität Braunschweig) initiated two funding programs to support the development of innovative teaching projects. These programs were funded by a larger governmental educational reform program (Qualitätspakt Lehre [Quality Teaching Act]; Federal Ministry of Education and Learning, 2021) to improve HE teaching. Furthermore, the funding programs aimed to develop, experiment with, and exchange ideas and knowledge regarding innovative teaching projects (Kauffeld et al., 2019). Innovative teaching projects often consist of educational technology combined with a pedagogical approach (Kauffeld & Othmer, 2019; see, e.g., Appendix, Tables 5 and 6). They usually involve two to four HE teachers who develop an idea to change their teaching; apply for funding to fulfill the aspired changes to their course; and, if approved, implement their innovative teaching idea within a given timeframe (Kauffeld et al., 2019; Feixas et al., 2018; Jütte et al., 2017). To ensure KT, the Technische Universität Braunschweig established a second funding program (called the transfer program) to promote the transfer of innovative teaching projects to other disciplines in the form of additional projects (Kauffeld et al., 2019; see, e.g., Appendix, Tables 5 and 6). No predefined number of components had to be adopted by the transfer recipient as a condition for funding. HE teachers were free to decide which components they wanted to adopt, adapt to their (and their students') needs, or reject. HE teachers had to apply for funding from either program by describing their projects in detailed proposals. There were usually more applicants than funded projects, and there was no defined number of projects for which funding had to be provided. The only limitation was the annual or semi-annual amount of funding (Kauffeld et al., 2019).

A jury of HE professors and student representatives evaluated the proposals based on different criteria: the benefits for students, the innovativeness of the concept, the connection to the university's strategy for teaching and learning, and the didactic and organizational coherence (e.g., Kauffeld, 2017; Technische Universität Braunschweig, 2016; Kauffeld et al., 2019). Additional selection criteria were the project's practicability, sustainability, and transferability (Kauffeld et al., 2019). The university aimed to achieve a greater impact of individual innovative teaching projects that might initially reach only a few students (see, e.g., Appendix, Tables 5 and 6) by supporting interventions that might lead to innovation diffusion. Through innovation diffusion, teaching ideas that aligned with the university's strategy could reach system-oriented sustainability. Therefore, the jury assessed the project's sustainability connected to the project's transferability to other subjects. Project funding usually included participation in several networking events and a training program designed to help HE teachers with the didactical setup and implementation of their specific teaching projects. Furthermore, networking events provided HE teachers with the opportunity to transfer knowledge and trade experiences with their colleagues (Kauffeld et al., 2019). In addition, projects were introduced and described in various newsletters and media formats (e.g., Technische Universität Braunschweig, 2021).

This type of connection between HE teachers and their innovative teaching projects is a two-mode educational innovation network. In this empirical case, KT was forced and fostered through the funding programs because the transfer of innovative teaching projects from one discipline (and HE teacher) to another discipline (and HE teacher) was the basis for additional funding and communication. Furthermore, KT was supported through networking events and training (Kauffeld et al., 2019). Hence, we argue that ties between HE teachers and their innovative teaching projects indicate KT in this empirical two-mode educational innovation network. Furthermore, this empirical case offers the possibility of investigating whether network structures, which enable efficient KT, can be created through funding.

2.2. Hypothesis on the Efficiency of Network Structures for KT

Social network analysis (SNA) is often used to examine the efficiency of network typologies on the diffusion of innovation and KT in the organizational and educational context. Many studies have identified network characteristics (e.g., clustering, short path length) that are particularly beneficial or disadvantageous for KT and innovation diffusion and can be used to evaluate whether an educational innovation network is working efficiently (Centola, 2015; Kezar, 2014; Mirriahi et al., 2012; Phelps et al., 2012). Centralization explains the extent to which a *whole* network is structured around central units (Scott, 2017), for example, individual HE teachers. Daly and Finnigan (2010) analyzed the social network structure between administrators in central offices and school principals in a "need of improvement" school district in the context of a large governmental educational reform program, "No Child Left Behind" in the US. This program tried to achieve (positive) changes for all subgroups of students by changing existing funding structures through testing, sanctions, and loss of both fiscal and human resources (Daly & Finnigan, 2010; Orfield et al., 2004). The study aimed to find indications for supporting or constraining change efforts in this school district. In order to achieve these goals, key stakeholders' communication and knowledge networks were analyzed, and a core-periphery (CP) measure was calculated (Daly & Finnigan, 2010).

The results revealed that communication and KT were highly centralized in the studied school district. Furthermore, only limited communication and KT occurred between and among central office and site administrators. Based on their qualitative and quantitative results, Daly and Finnigan (2010) argue that centralization has adverse effects on educational reform efforts and educational change. In line with these findings, scholars argue that learning occurs in CoPs when individuals in the periphery of a network move and participate at the network's core (Lave & Wenger, 1991; Mirriahi et al., 2012; Wenger, 1998). Daly and Finnigan's (2010) study varies from the current case study in different aspects; that is, it analyzes change processes in the school and not the HE context. They study one-mode networks with a focus on administrators rather than teachers. However, in this study, the informal KT network structure is visualized, and the SNA results are used to derive implications for network interventions.

Furthermore, the study's results indicate that an overall centralized network structure might inhibit KT and change. Studies on the social network structure of CoPs (Ma et al., 2019) suggest similar connections. Ma and colleagues (2019) found that CoPs in which evidence-based instructional practices were adopted were less centralized and more connected than non-adopting CoPs. Hence, communication about teaching was more likely to flow through a small number of organizational members in the non-adopting CoPs (Ma et al., 2019).

In the context of educational innovations, educational reform programs support KT between HE teachers through networking events (Kauffeld et al., 2019). Hence, these programs allow the creation of various connections between previously unrelated subgroups of HE teachers (e.g., from different departments). Such connections would be reflected in an overall decentralized network structure. Hence, we argue the following:

Hypothesis 1 (H1): An empirical educational innovation network (promoted by an educational reform program) should display a decentralized network structure.

Rogers's (2003) innovation diffusion theory states that people need to be connected for innovation and KT to take place. If HE teachers did not interact with one another, they would not learn (as deeply) about innovative teaching ideas and could never adopt them in their practice. The level of connectedness in a network can represent the level of clustering. Clustering describes the degree to which nodes in a network (e.g., HE teachers) tend to form densely connected groups.

This tendency has often been found in real-world networks (Opsahl & Panzarasa, 2009). Clustering promotes collaboration and risk-sharing, improving creativity and innovation (Fleming et al., 2007). Furthermore, clusters may enhance trust between teachers, which is essential for efficient exchange in educational change efforts (Daly et al., 2014). Clustering is one parameter that defines "small-world networks." The small-world paradigm proposes that most nodes in a social network are to some extent connected (Opsahl et al., 2017; Steen et al., 2011; Milgram, 1967). Studies indicate that networks with small-world characteristics can be beneficial for KT (Ansell et al., 2017) and innovation diffusion (Cowan & Jonard, 2004).

Another important feature of small worlds is a small path length. The average path length is the mean number of steps in a network an individual needs to take to reach any other network member when taking the shortest path (Ansell et al., 2017). Let us assume that an HE teacher hears about a specific innovative teaching project and wants to contact the project initiator. The smallest number of individuals who know each other is called the "shortest path." In structural terms, short paths in a network can be created through individuals with a high betweenness centrality. Betweenness centrality is the extent to which an individual connects other individuals and subgroups in a social network. Individuals with a high betweenness centrality can act as "gatekeepers" or "bridges."

On the one hand, such individuals can control the flow of information, which might inhibit the diffusion of innovation (Rogers, 2003). However, studies show a positive relationship between technology adoption and the betweenness centrality of HE instructors (Mirriahi et al., 2012). Based on their quantitative and qualitative research results, Mirriahi and colleagues (2012) argue that instructors with high betweenness can assist with the flow of information and innovation diffusion across their departmental network. We argue that HE teachers who receive funding for their innovative teaching projects profit from active KT because they get more recognition in their educational community if others adopt their ideas. Hence, they do not need a central network position (a high betweenness centrality) to gain a competitive advantage.

On the contrary, the visibility of innovative teaching and its recognition acts as motivation for the innovators (Jütte et al., 2017) and might give them advantages for achieving career goals (e.g., through teaching awards). Hence, HE teachers with a high betweenness centrality might positively support KT between different clusters in a social network. Studies indicate that long bridges in social networks can support the diffusion process because they facilitate innovation diffusion and connect different subgroups. Hence, one contact (HE teacher) might efficiently diffuse a novel (teaching) idea. However, some diffusion processes (e.g., the diffusion of complex knowledge) need social reinforcement. Social reinforcement can succeed through wide bridges, where ideas can travel through *many* short paths in a network (Centola, 2015; Centola & Macy, 2007). Through wide bridges, more connectivity can occur, which might reduce the path length in a network. Hence, both structures, high connectivity (through high clustering) and a short path length, are beneficial for innovation. High clustering in a network could help develop diverse and innovative ideas, whereas a short average path length in a network might be beneficial for transferring those ideas (Uzzi et al., 2007; Uzzi & Spiro, 2005).

Studies on the social network structure of CoPs in the educational context (Ma et al., 2019) also reveal that CoPs that adopted innovative pedagogical practices had lower breadth than non-adopting CoPs. These results connect to the short path length argument. They indicate that communication in professional teacher communities is more efficient if the information between two people does not flow through many other individuals. Thus, we postulate the following:

Hypothesis 2 (H2): Educational innovation networks (promoted by an educational reform program) display small-world network characteristics.

Studies analyzing "small-worldness" in networks are often criticized for using secondary data, which is commonly the primary source for two-mode networks (e.g., scientific collaboration networks constructed using author affiliations from scientific papers). Using secondary data from documents or databases has several advantages. Above all, it is economical and time-efficient. Researchers do not need to acquire an extensive sample, and participants do not need to fill out long network surveys. Furthermore, memory effects can be avoided because participants do not need to remember with whom they communicated and on which matters. However, one limitation of using secondary data is that it is challenging to examine informal exchange relationships (Steen et al., 2011). Newman (2001) argues that in scientific collaboration networks, coauthorship between scientists who worked on different projects together (e.g., scientific papers) may account for real acquaintance between them and therefore lead to better collaboration or cooperation on further projects. Recurring collaboration on different projects can therefore reinforce the relationship between actors. This tendency in two-mode networks can be analyzed by the reinforcement coefficient showing the level of cooperation on different projects between the same people in the network. We can transfer Newman's (2001) argument to the context of educational innovations in HE. There is an indication for real collaboration and exchange between HE teachers where working together on one innovative teaching project makes it likely to also work together on a second or third innovative teaching project. Working on several innovative teaching projects together implies the diffusion of innovation and KT. Moreover, HE teachers who know each other and have a high level of teaching competence are likely to work together more often to use synergies. Therefore, we postulate the following:

Hypothesis 3 (H3): Educational innovation networks (promoted by an educational reform program) display strong reinforcement.

The componential theory of creativity states that knowledge in a specific domain is the foundation for any creative action within that domain (Amabile, 2012) and, thus, innovation. As we argued before, innovative teaching projects can consist of various didactical, methodological, and technical components (e.g., game-based and practical learning; Kauffeld & Othmer, 2019; see, e.g., Appendix, Tables 5 and 6). Therefore, HE teachers can develop a significant amount of experience and knowledge in the different methodological and didactical areas of their innovative teaching project(s). Thus, the development and success of an educational innovation depend not only on the formation of a functioning network but also on HE teachers' knowledge in that specific field. Studies have shown that the greater a co-worker's experience in a particular area, the greater the probability that others will use them as sources of knowledge and want to learn from and connect with them (Škerlavaj & Dimovski, 2006). Hence, HE teachers who adopt (various) educational innovation elements (technological or didactical elements) might possess more knowledge about these elements. One can assume that knowledge about different educational innovation elements (e.g., knowledge about peer education and game-based learning) acts as a resource and gives HE teachers a strategic advantage in networking with many other HE teachers. This strategic advantage should be reflected in the educational innovation network by a better network position and many contacts. Thus, we postulate the following:

Hypothesis 4 (H4): HE teachers with greater knowledge about different educational innovation elements have more contacts in the network and thus a greater degree parameter.

3. Methods

3.1. Sample and Procedure

We collected data on a binary two-mode educational innovation network. The primary node set consisted of HE teachers and other staff members in HE (N = 208) who participated in innovative teaching projects between 2012 and 2017. The secondary node set consisted of innovative teaching projects created by the participants (N = 91). A typical innovative teaching project consisted of two to four HE teachers (Figure 1), usually one professor who supported the project and one to three staff members who developed and implemented the innovation. To acquire the relevant network data, several databanks and documents (e.g., project presentations, registration data) were analyzed. Since teaching staff were not interviewed directly, no data were available concerning demographics.

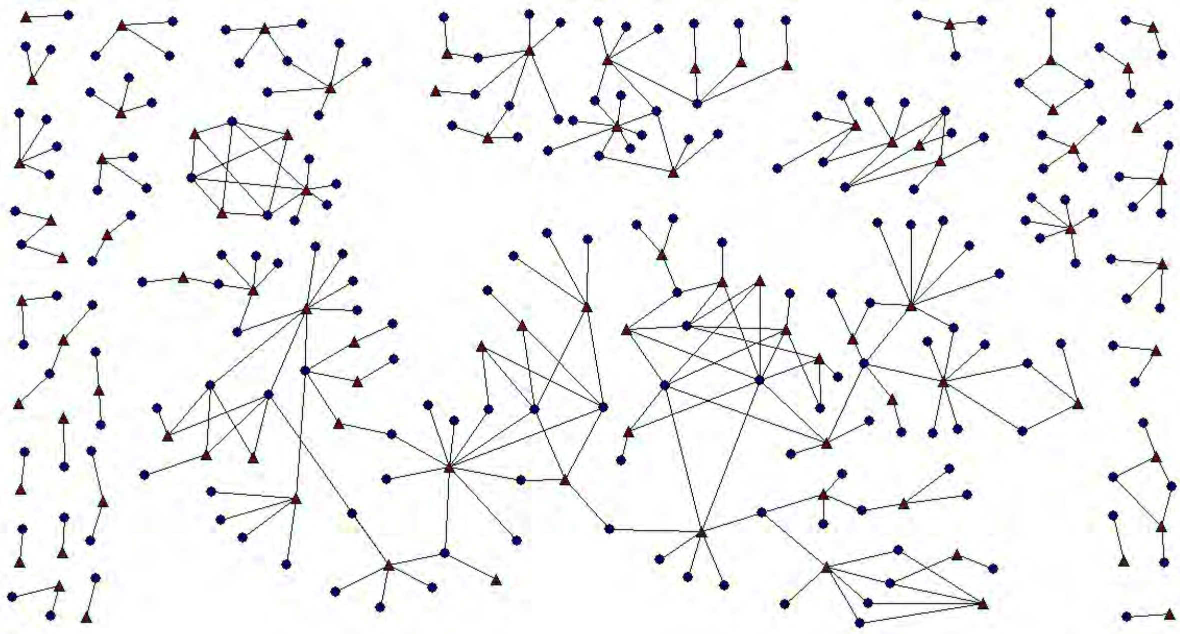

Figure 1. Visualization of the educational innovation network (2012–2017). Primary-mode nodes (blue circles) represent the participants (HE teachers) involved in an innovative teaching project. Secondary nodes (red triangles) represent innovative teaching projects. The figure was created with NetDraw (Borgatti, 2002).

3.2. Attributes of HE Teachers Based on Educational Innovation Elements

To obtain deeper insight into the dynamics of the educational innovation network, we wanted to analyze its structure and the attributes of the network nodes. The innovative projects in our two-mode network consist of different didactical, methodological, and technological teaching elements. In the empirical case analyzed in this study, the university's strategy regarding teaching and learning focused on game-based learning, mobile learning, and visualization (Kauffeld, 2017; Kauffeld et al., 2019). Based on this strategy and current trends in the field of education (inverted classroom and practice-, scientific-, and problem-based learning; Kauffeld et al., 2019), we created a list of relevant educational innovation elements.

In the next step, the innovative teaching projects were categorized according to these educational innovation elements. This was done by the department head of the funding programs at the university level. Two innovative teaching projects did not fit into this categorization; to keep the number of categories manageable, we did not expand the lists of categories to include these projects and considered the attributes of these projects as missing values. The matching of HE teachers with projects allowed us to assess the experience with educational innovation elements as attributes for the HE teachers. For example, the first project, "Eyetracking Spatial Experiences," was categorized as an innovative teaching project with scientific-based and mobile learning elements (Appendix, Table 5). We assumed that the HE teachers involved in the development and implementation of "Eyetracking Spatial Experiences" had knowledge about these educational innovation elements and added them as HE teachers' attributes. Furthermore, we calculated the number of innovative educational elements for each HE teacher, using this number as a measurement for general knowledge about educational innovations.

3.3. Data Analysis

In the following paragraphs, we describe the data analysis methods and the central network characteristics that we analyzed. In two-mode networks, not all network parameters can be studied directly. Hence, the network's projection plays a crucial role in data analysis (Opsahl et al., 2017). This study aimed to analyze the efficiency of two-mode educational innovation networks for KT and learning. The efficiency of networks is a complex concept that is difficult to evaluate (Rogers et al., 2001). One methodological approach is to compare empirical network structures with a random network based on empirically found network characteristics (Erdös & Rényi, 1959; Newman, 2001; Opsahl, 2013; Watts & Strogatz, 1998). We calculated the same network parameters (e.g., clustering) to compare the observed network with random networks. Calculations were carried out using the tnet (Opsahl, 2011) and igraph packages in R (Csardi & Nepusz, 2006) and UCINET 6 (Borgatti et al., 2002).

3.3.1. Projection

Since only a few analyzing methods exist for two-mode networks, they are usually transformed into weighted one-mode networks through projection (Padrón et al., 2011). Projection is a process of transferring the structure and information of a two-mode network into a weighted one-mode network. The process is illustrated in Figures 2 and 3. Newman (2001) offered a specific projection method after analyzing collaboration networks between researchers and arguing that connections between researchers who worked on the same paper with only two authors must be more intense than connections between people who worked with several coauthors. We assumed that the ties between people who worked together on smaller projects consisting of only a few people would be stronger in our empirical network. Therefore, we used the Newman method of projection for further calculations (Opsahl, 2013).

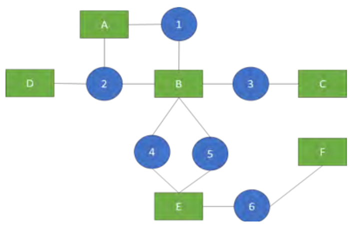

Figure 2. Two-mode network consisting of organizational members (green rectangles) and innovative teaching projects (blue circles). Figure based on Opsahl (2012a, 2013).

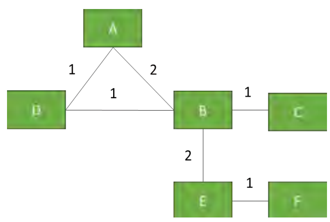

Figure 3. Projection of the two-mode network in Figure 2, with weights.

3.3.2. Random Networks

One of several ways of creating random networks based on an empirical network structure is the Erdös–Rényi random graph. This method calculates random network parameters to assess the small-world coefficient (Ansell et al., 2017). The Erdös–Rényi (Bernoulli) model sets only the number of ties in the network and gives every node the same probability of formation, which is seldom the case in real-world networks. Therefore, we used a tie-reshuffling method (Opsahl, 2013; Opsahl et al., 2017), which reshuffles the typology of the network and creates a random network with the same degree distribution as the observed network.

3.3.3. Measures

CP Measure

Networks with a high CP structure have a core of individuals who are densely connected to each other, and a periphery with individuals who are less connected to the core (Everett & Borgatti, 1999; see Figure 4 for an example). The CP measure compares the empirical network with an ideal, highly centralized CP model and reports the correlation of the two centralized structures (Daly & Finnigan, 2010). The CP measure is a centrality measure because "all actors in a core are necessarily highly central as measured by virtually any measure" (Borgatti & Everett, 1999, p. 393). Hence, we use the CP measure to evaluate the centralization of the educational innovation network. To analyze the CP measure, we first projected our two-mode network into a one-mode network.

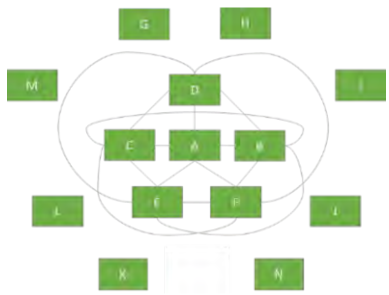

Figure 4. Example of a hypothetical network with a high CP structure, in which the core consists of only a few nodes (A–F) and the other nodes are in the periphery (G–N). In the context of educational innovations in HE, this would be a structure in which a few innovative teaching projects are transferred a lot. However, most projects are never transferred to other subjects.

Small-World Network

Small-worldness can be analyzed by looking at a network's clustering and path length (Opsahl et al., 2010; Opsahl, 2013; Opsahl et al., 2017). Clustering is measured in a member-project two-mode network as a global tendency of the whole network to cluster, as seen in Figure 5. We noted one 4-cycle connecting two individuals and two projects. Connecting organizational member B to Project 2 in the 3-cycle may seem to be a form of clustering (Figure 6). However, only two individuals are included in this structure, and in one-mode networks this would not be considered clustering and would correspond to the concept of triadic closure (Opsahl, 2013). Therefore, Opsahl (2013) proposes to measure (global) clustering by examining the closure between three nodes of the primary node set (e.g., HE teachers). The clustering coefficient we used to analyze our hypotheses does not require a projection of the two-mode network; it is defined as the number of closed 4-paths (of the primary nodes) divided by the number of all 4-paths (of the primary nodes) in the network.

To calculate the path length in a two-mode network, one can use the weighted short-path algorithm (Opsahl et al., 2010) after projecting the network into a weighted one-mode network. The algorithm considers the cost of the connections and finds the "path of least resistance" by calculating the sum of the inverted tie weights (Opsahl et al., 2010, p. 12). Specifically, the stronger the tie, the lower the cost of using this tie (e.g., to transfer information).

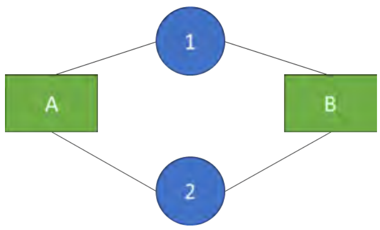

Figure 5. A 4-cycle connecting two organizational members (A and B) and two innovative teaching projects (1 and 2). Figure based on Opsahl (2012b, 2013).

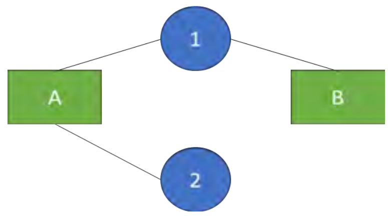

Figure 6. A 3-cycle in a two-mode network shows that two organizational members are working on a joint innovative teaching project (1) but not on the second project (2). Figure based on Opsahl (2012b, 2013).

One way to estimate whether the existing network is a small-world network is through the small-world coefficient. This measure is calculated as the ratio of clustering coefficient to average path length from an empirical network—in our case, an educational innovation network—divided by the similar ratio of a random graph with the same number of nodes (e.g., Ansell et al., 2017). We projected our network and used the tie-reshuffling algorithm to create a random graph for the small-world coefficient (Opsahl, 2013; Opsahl et al., 2017): $Q = (CC_{educationalinnovationnetwork}/CC_{random})/(L_{educationalinnovationnetwork}/L_{random})$.

Using the small-world coefficient as a statistical method to determine the existence of a small-world network is controversially discussed in the literature (Opsahl et al., 2017). This coefficient is, for example, "sensitive to large differences between the results for path length and those for clustering," and "there is a fundamental ambiguity regarding what makes a random network appropriate for comparison" (Opsahl et al., 2017, p. 151). The main limitation is that the coefficient does not allow evaluation of whether the obtained values from the network are representative of the population of random networks. Therefore, we also followed Opsahl and colleagues' (2017) framework of network efficiency to evaluate whether our educational innovation network is a small-world network. We analyzed our two-mode network and used the tie-reshuffling option to generate 1,000 random networks. Then, we checked for normal distribution of the data and calculated confidence intervals (CIs) if possible.

Reinforcement

Reinforcement can be calculated by looking at the number of 4-cycles in a member-project two-mode network and then

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dividing this number by the number of 3-paths in the network. In our example, 3-paths would be two HE teachers working together on only one innovative teaching project, like "Eyetracking Spatial Experience" (Appendix, Table 5). A 4-cycle would show collaboration on at least two different innovative teaching projects like "Eyetracking Spatial Experience" and "Interdisciplinary Studio for Communicational and Observational Research" (iSCOR) (Appendix, Table 5) and would therefore indicate that there might be real acquaintance and collaboration between those two HE teachers (Opsahl, 2013).

Centrality

We analyzed the nodes' degree to determine the role of knowledge about different educational innovation elements in HE teachers' network position and popularity (H4). Degree measures how many connections a node has in a network (Newman, 2005). In weighted networks, degree is often calculated by summing the weights of a node's connections. This might cause nodes with a different number of contacts to have the same degree parameter. To address this problem, a tuning parameter alpha can be used, which "determines the relative importance of the number of ties compared to tie weights" (Opsahl et al., 2010, p. 8). "Hence, for $\alpha < 1$, a shorter path composed of weak ties […] is favored over a longer path with strong ties" (Opsahl et al., 2010, p. 14).

In our example, we projected the two-mode network into a weighted one-mode network and used the tuning parameter $\alpha = 0.5$ when calculating the HE teachers' degree. In doing so, we considered the number of ties HE teachers have in our educational innovation network to be more important than the number of innovative teaching projects they are involved in and share with their contacts. Next, we used the amount of knowledge HE teachers possessed about educational innovation elements to categorize them into three groups (HE teachers with knowledge about one, two, or three educational innovation elements). Then we compared these groups regarding their network degrees.

4. Results

The correlation between the centrality structure for the empirical educational innovation network with a perfect CP model is moderate (0.314), which can be interpreted as support for H1. This result demonstrates that the educational innovation network did not display a prominent centrality structure. The result is supported by the visualization of the educational innovation network (Figure 7). One can see a decentralized network with several nodes that function as brokers between different subgroups. Table 1 shows the density of all four types of relations between core and periphery. Only a small core where all HE teachers are interconnected was identified (density = 1.0). Few connections between the HE teachers in the periphery are evident (density = 0.023), and even fewer between HE teachers in the periphery and the core.

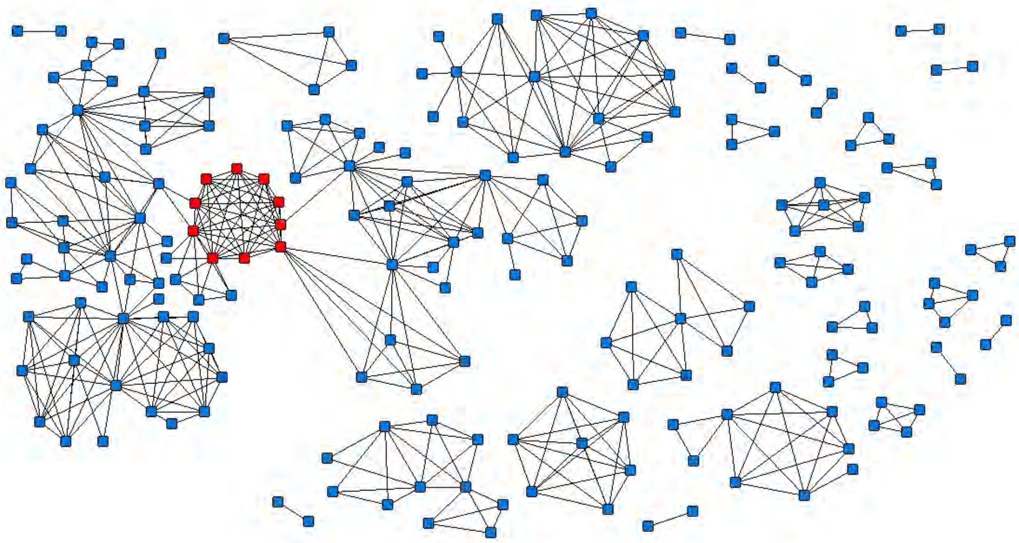

Figure 7. Weighted one-mode network (projection of the two-mode educational innovation network). Illustrated are only HE teachers. Periphery nodes are blue; core nodes are red. The graphic was created with NetDraw (Borgatti, 2002).

Table 1. Density Matrix between Core and Peripheral HE Teachers

	Core	Periphery
Core (*N* = 11)	1.000	0.009
Periphery (*N* = 188)	0.009	0.023

Note: Network density is the total number of ties divided by the number of all possible ties.

Descriptive results (Table 2) of the core members (*N* = 10) show that the core consisted of five professors and five HE teachers at the doctoral or postdoctoral level who belonged to five institutes and three faculties. They worked on seven innovative teaching projects. Furthermore, we looked at the HE teachers' attributes regarding their knowledge about educational innovation elements (e.g., game-based learning), which did not appear to be equally distributed within the network (Appendix, Figures 8–15). In the whole network (Figure 8), many teachers worked on innovative teaching projects that focused on mobile learning, practical learning, visualization, and game-based learning components (Table 2; Appendix, Figures 8–15). This is largely reflected in the core of the network, with the exception that only one member worked on projects with visualization elements. One can see that HE teachers who worked with mobile learning (Appendix, Figure 14) and practical learning (Appendix, Figure 15) established many ties in the educational innovation network and clusters. Such a structure can also be found to some degree in the network of HE teachers who worked with game-based learning (Appendix, Figure 11). Furthermore, peer learning was often part of the innovative teaching projects in the overall network, whereas no HE teacher in the core worked on a project with such a component (Table 2). Due to the limited number of core members, the rankings of the educational innovation elements used in the whole network and in the periphery are identical.

Table 2. Ranking of Educational Innovation Components in the Educational Innovation Network, Based on the Number of HE Teachers Who Use Such Components in Innovative Teaching Projects

Educational Innovation Component	Number of HE Teachers in the Network	Number of HE Teachers in the Core	Number of HE Teachers in the Periphery	Sum of Isolated HE Teachers and HE Teachers in Dyads
Mobile learning	96	6	90	10
Practice learning	91	3	88	6
Visualization	48	1	47	16
Game-based learning	37	5	32	7
Peer learning	32	0	32	4
Scientific-based learning	25	4	21	7
Inverted classroom	18	1	17	7
Problem-based learning	15	0	15	3

Note: The total number of HE teachers differs from the number of HE teachers in the network because the same teacher can work on a project that might consist of several elements (e.g., scientific-based and problem-based learning). Components in bold represent elements that correspond to the university's strategy (Kauffeld, 2017; Kauffeld et al., 2019).

In our second hypothesis, we assumed that an educational innovation network displays small-world characteristics. The small-world coefficient was calculated by the ratio of the empirical coefficient (0.093) to a random clustering coefficient (0.04), as well as average path length for the empirical educational network (3.37) and a random network (3.85). The small-world coefficient was 2.66 and thus larger than one, indicating that our educational innovation network is a small-world network. We also used Opsahl and colleagues' (2017) framework to analyze small-worldness. Scholars argue that small-worldness can be assumed only if a network has both more clustering and a shorter average path length than randomized networks. For 1,000 randomized networks, we calculated the Anderson–Darling test, which showed a normal distribution for clustering (0.503, $p > 0.05$) but not for path length (1.545, $p < 0.000$). Therefore, we calculated CIs only for the clustering parameter. The clustering parameter of our empirical educational innovation network (CC = 0.093, $p < 0.000$) is outside the CI [0.088; 0.089] of the 1,000 randomized networks (Appendix, Figure 16), which can be interpreted as support for our hypothesis, since clustering in our network was higher than can be assumed by chance. However, we could not analyze whether the network exhibited clustering and small path length simultaneously. Due to the small-world coefficient and clustering results, we argue that there is partial support for H2.

In our third hypothesis, we predicted that the reinforcement coefficient for efficient collaboration between project partners would be larger in our empirical educational innovation network than in a random network. The reinforcement parameter in our empirical network was 0.275 and therefore greater than that of one random network (0.017) and greater than the mean of 1,000 randomized networks, which was zero (range from 0 to 0.040). This finding indicates a greater amount of reinforcement in the empirical educational innovation network than in randomized networks, supporting H3.

In our fourth hypothesis, we assumed that HE teachers with greater involvement in different educational innovation elements are more popular and have a greater number of connections. Our data confirmed this assumption in the first place ($F(2,193) = 6.60$, $p = 0.002$ (Table 3)). Post hoc analysis (Table 4) showed that HE teachers with involvement in two educational innovation elements had a greater degree ($M = 2.89$, $SD = 2.10$) than HE teachers with one educational element ($M = 1.99$, $SD = 1.17$). However, HE teachers with involvement in three educational elements ($M = 2.12$, $SD = 1.15$) had a lower degree than HE teachers with involvement in two educational elements ($M = 2.89$, $SD = 2.10$). HE teachers with involvement in one or three educational elements did not differ significantly. Thus, we found partial support for H4.

Table 3. Weighted Degree with $\alpha = 0.05$

	SS	*df*	*MS*	*F*	*p*
Between the groups	34.949*	2	17.475	6.597	0.002
Within the groups	511.230	193	2.649		
Total	546.179	195			

* $p < 0.05$.

Table 4. Post-Hoc Tests with Bonferroni Correction

(I) Condition	(J) Condition	Average Difference (I-J)	SE	p	95% CI
1	2	−0.900*	0.263	0.002	[−1.54, −0.27]
	3	−0.136	0.316	1.000	[−0.90, 0.63]
2	1	0.900*	0.263	0.002	[0.27, 1.54]
	3	0.764*	0.309	0.043	[0.02, 1.51]
3	1	0.136	0.316	1.000	[−0.63, 0.90]
	2	−0.764*	0.309	0.043	[−1.51, −0.02]

*$p < 0.05$.

5. Discussion

Our study aimed to analyze whether efficient KT occurs and can be measured in two-mode educational innovation networks. Although SNA has been identified as an essential method for LA (e.g., Gruzd et al., 2016; Avella et al., 2016; Leitner et al., 2017), two-mode networks are hardly analyzed (Dado & Bodemer, 2017). To our knowledge, this is the first study using SNA to examine two-mode educational innovation networks (Kezar, 2014).

Researchers often use indirect techniques to collect two-mode network data and do not ask organization members (e.g., students or teachers) directly about their KT and learning processes. Thus, the tie connections in the network are usually not collected through a survey. This data collection approach presents the researcher with the challenge of collecting or using network data in which network ties already reflect KT. Hence, we argue that researchers cannot study KT in all two-mode networks. Instead, researchers need to give extensive thought and argument to why the ties in an investigated two-mode network represent KT and learning. This study tackled this challenge by using a case-study approach (Rowley, 2002). We described the nature of the nodes and ties in the two-mode network and analyzed network structures, which have been described in other studies as beneficial for KT and innovation diffusion (e.g., Ansell et al., 2017; Cowan & Jonard, 2004; Phelps et al., 2012). Furthermore, we compared the empirical network structures with random structures to determine whether the observed structures are more prominent than can be assumed by chance (Opsahl, 2013; Opsahl et al., 2017). Our empirical results support the assumption that KT occurs in two-mode educational innovation networks funded and supported through educational reform programs.

We found indications for a decentralized network structure. The visualization of the projected one-mode network of the HE teachers illustrates one small core connected to several other clusters of HE teachers. Therefore, no HE teachers had such a structural advantage over other network members that it enabled them to withhold resources, information, or knowledge, which would be disadvantageous for innovation diffusion and KT (Rogers, 2003). Core members worked on various innovative teaching projects. They belonged to different institutes and had different statuses in the university. These results mean that the funding programs were able to fund various projects and departments and did not create a structure in which only one organizational subunit or discipline, or only high-status members of the organization (e.g., professors), have a high structural advantage over others. This diversity can lead to new perspectives, which can be beneficial for KT and the diffusion of (educational) innovation (Bassett-Jones, 2005).

The findings on a decentralized network structure in our empirical educational innovation are, to some degree, supported by the results on clustering, path length, and the small-world coefficient. Results showed greater clustering in the educational innovation network than can be assumed by chance. Clustering is beneficial for innovation because cohesive subgroups can “mobilize quickly” and “bring ideas to fruition” (Opsahl et al., 2017, p. 151). Indeed, a short path length may facilitate the diffusion of such ideas. We found that HE teachers reached each other in the empirical educational innovation networks via four steps. An HE teacher who requires information and knowledge was only a few network contacts away from every other member of the community. This result indicates the possibility for fast KT. However, this feature was not more pronounced than in random networks. The network visualization reflected several small and larger clusters in the network, but bridges (nodes that connect otherwise unconnected ties) that provide “shortcuts” through the network and that may enhance the transfer of complex knowledge (e.g., about education innovation; Centola & Macy, 2007, p. 704) appeared underdeveloped. Visually, we inferred that bridges with long ties (which connect spatially distant nodes in the network) as well as wide bridges (which contain many ties and are spatially close) might have led to greater connectivity in the network (see Centola and Macy (2007) for the concept of diffusion and bridges). This result indicates that different teacher subgroups need more actors that have contacts with other subgroups or individuals. KT could be supported through more connections to isolated subgroups or to HE teachers in the periphery of the network.

In this study, we also aimed to analyze how knowledge about educational innovation elements (e.g., game-based learning) connects to the structure of the educational innovation network. Partly corresponding to our hypothesis, we found an inverted U-shaped relationship between HE teachers' knowledge about educational innovation elements and their network degree. This result suggests that, to a certain degree, HE teachers who have a great amount of knowledge about educational innovation elements have a structural advantage because other HE teachers are more likely to use them as a source of knowledge (Škerlavaj & Dimovski, 2006). However, we found that "too much" knowledge reduces the positive effect, as seen by the inverted U-shaped relationship.

The inverted U-shaped relationship between knowledge and network degree we found makes sense when considering that KT requires resources, such as time (Hansen, 1999). We defined knowledge as the number of educational innovation elements HE teachers work within in their projects. If an HE teacher works in innovative teaching projects consisting of more than two components (and that are therefore likely to be more complex), they will probably need more time to explain ideas and concepts. The resulting reduction in KT capacity, in turn, is reflected in the inverted U-shaped relationship between knowledge and degree. Therefore, a moderate complexity seems to help transfer an innovative teaching project to other colleagues or study fields at HE institutions.

Moreover, our descriptive analyses showed that the number of educational innovation elements used by the HE teachers varies substantially in the network. Educational innovation elements that correspond to the university's strategy on teaching and learning (e.g., game-based learning, mobile learning, and visualization; Kauffeld, 2017; Kauffeld et al., 2019) were prominent in the network. Practical learning as an educational innovation element was also widely used, reflecting current trends in the education sector (Kauffeld & Othmer, 2019).

Furthermore, HE teachers using specific educational innovation elements (e.g., mobile learning) achieved greater connectivity in the network, whereas certain educational innovation elements (e.g., problem-based learning) were largely used by HE teachers in the periphery of our educational innovation network. Again, this could be explained by the complexity of the educational innovation elements; those in the periphery may be less complex, and therefore HE teachers may have no further need for communication and exchange. Another reason for our findings on the CP structure might be that HE teachers who work with less popular educational innovation elements may have more difficulty finding other HE teachers with similar projects to exchange problems, ideas, solutions, and general knowledge. Lastly, differences in the prevalence of educational innovation elements in the network could result from different levels of support (through events and training) regarding certain elements. These results demonstrate which knowledge is prevalent in the educational innovation network and how knowledge influences individual network positions.

5.1. Practical Implications

In line with the general benefits of LA research (Avella et al., 2016), our findings have several implications for various stakeholders (e.g., HE teachers, administrators; Romero & Ventura, 2013) in the educational sector. HE teachers can use the study's results to reflect on their teaching concepts and networking behaviour. Although our study shows that certain network structures such as clustering foster efficient KT, the results also indicate potential for greater connectivity in the network. An increase in connectivity and density supports the diffusion of information in networks (Singh, 2005). To provide educational innovation networks in general with more "shortcuts" (Centola & Macy, 2007, p. 704), those responsible for the funding programs could aim at introducing HE teachers directly to each other, adding to the practice of general networking events (Kauffeld et al., 2019).

We identified that innovative teaching projects with two rather than one or three educational innovation components are related to a better network position. Hence, it might be beneficial for HE teachers to create teaching concepts of medium complexity and administrators to provide additional support for more complex projects. Practitioners could use our results to provide additional support to HE teachers using educational innovation elements connected to peripheral network positions (e.g., problem-based learning). Hence, our study might influence administrators' decision-making process and provide them with ideas on network interventions that can support educational change.

Overall, our findings demonstrate that educational innovations designed for individual courses can be strongly diffused through networks. KT increases the visibility of the innovative teaching projects in the professional community and the visibility of HE teachers as educational innovators. Despite the effort to design and implement educational innovations (e.g., Towndrow et al., 2010), these results should motivate HE teachers to participate in educational innovation networks since greater visibility might create more career opportunities (e.g., through more professional contacts or teaching awards). Through reflecting on their current teaching (and support) practices, HE teachers can enhance their teaching and create better student learning experiences.

5.2. Limitations and Further Research

This study's main limitation is the generalizability of the results to other contexts due to the case-study approach. However, such case-study approaches are common in LA and social network research and provide detailed insight into the social network structure in university departments or CoPs (e.g., Mirriahi et al., 2012; Daly & Finnigan, 2010). Furthermore, we analyzed secondary data on innovative teaching projects and member affiliation. We did not ask participants whom in the educational innovation network they actively shared their ideas with. Therefore, we cannot draw conclusions about the member-member network behind the two-mode network. As other researchers have argued, constructing a network and identifying small-worldness does not mean actual information flow is occurring in that network (Steen et al., 2011). However, we demonstrated that the reinforcement parameter is greater in our empirical network than in a random network, indicating more cooperation between HE teachers on the same innovative teaching projects in the empirical education innovation network than can be assumed by chance. These results suggest real exchange and efficient KT in our network (Newman, 2001). Furthermore, by analyzing secondary data, we demonstrated that university practitioners and LA researchers can implement an economical form of evaluation that is not based on subjective network data.

Our results reveal the existence of important network features for innovation diffusion. Studies show that other network parameters like homophily also influence innovation diffusion (Centola, 2011). Studies in the HE context analyze the role of homophily in departmental networks (Quardokus & Henderson, 2015). Further research has to be conducted to understand the role of homophily for innovation diffusion in two-mode and one-mode educational innovation networks. Furthermore, additional research is necessary to understand the role of different network centrality measurements (Mirriahi et al., 2012) in different types of teacher networks in innovation diffusion and KT processes.

Using an expert rating on educational innovation elements of the innovative teaching projects allowed us to gain insight into the kind of knowledge that is transferred in the network. We used educational innovation elements that, to some extent, are used in other studies (García-Peñalvo et al., 2015). However, we cannot assume that this list of educational innovation elements is complete. Instead, we developed these categories for our specific empirical case, meaning that other empirical studies would need to adapt or supplement this categorization if necessary. Further research is necessary to examine the accuracy of the definition of the HE teachers' knowledge in our study and to determine whether this corresponds to HE teachers' qualitative self-assessments.

In this study, we compared our empirical network to networks that were reshuffled based on our empirical network and its initial degree distribution (Opsahl, 2013; Opsahl et al., 2017). We want to point out that this method of generating randomized networks is a potential limitation of our study. Scholars have already discussed the pitfalls of different procedures for creating randomized networks (e.g., the fit between the randomization procedure and the research question; see Hobson et al., 2021). Another different method of reshuffling data from the one used in this study is the weight-reshuffling procedure (Opsahl, 2013; Opsahl et al., 2008). This procedure reshuffles the weights globally in the network while maintaining the original structure of the empirical network (Opsahl et al., 2008). It is also possible to reshuffle weights locally for each node across its outgoing ties by using the local weight-reshuffling procedure (Opsahl et al., 2008). These two procedures generate random networks with a lower degree of randomization than the tie-reshuffling procedure applied in this study. However, they might be more appropriate for studying educational innovation networks because connections in the empirical network might be more specific to groups of HE teachers (e.g., departments). Choosing procedures that even better preserve the original typology of the empirical network might lead to more reliable results. Future research should focus on different randomization procedures to analyze the efficiency of educational innovation networks regarding KT and innovation diffusion.

Learners can profit from LA research through (direct) feedback on the learning process (Greller & Drachsler, 2012). In this study, it was not possible to study the effect of innovative teaching projects (and educational innovation elements therein) on students' performance. Research suggests that a lack of evidence regarding the effectiveness of LA technology on student performance and retention inhibits the adoption process (e.g., predictive LA; see Herodotou et al., 2019). Further research on the effect of different innovative teaching projects (and related educational innovation elements) on student performance is important to promote adoption. Nevertheless, teachers play a crucial role in student performance and satisfaction (Glerum et al., 2021; Grohmann et al., 2021; Rienties et al., 2018), and hence it is important to look at their role in the educational process. Furthermore, we analyzed data on HE teachers in their role as learners and educators, providing them with research results that might enhance their reflection on their networking behaviour and applied teaching methods.

5.3. Conclusion

Our results provide important insight into KT in two-mode networks between HE teachers and their innovative teaching projects. Our results are in line with other studies that have demonstrated how the implementation of funding structures could support the success of innovative teaching projects (e.g., Feixas et al., 2018). Using SNA in our study allowed a deeper understanding of the social structure that supports KT regarding educational innovations. Indeed, only a few studies have examined KT in organizations via member-member networks, and therefore one-mode networks, in the educational context (e.g., Daly & Finnigan, 2010). Even fewer studies have used SNA and one-mode network data, in particular, to analyze innovative teaching projects in HE (Jütte et al., 2017). To our knowledge, this is the first paper to analyze a member-task network in HE, demonstrating that project structures are suitable for successful KT of complex knowledge such as innovations. By choosing this approach, we contribute to the theoretical framework of knowledge reservoirs (e.g., Arrow et al., 2000; McGrath & Argote, 2001). In summary, we found support for the idea that innovation diffusion and

KT can successfully occur in educational innovation networks supported through educational reform programs.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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