

# Uncovering the multidisciplinary nature of technology management: journal citation network analysis

Hakyeon Lee

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**Abstract** Technology management (TM) is multidisciplinary in nature. This paper investigates the multidisciplinary characteristics of TM through journal citation network analysis. The TM network composed of ten TM specialty journals and relevant journals of other disciplines is constructed based on their citation relationships. In particular, the relatedness index is employed to capture the citation relationships between journals with consideration of different journal sizes. Scrutinizing the network reveals what disciplines have contributed to TM and to what disciplines TM has contributed. The role of TM journals in exchanging knowledge with other disciplines is also identified by using brokerage analysis. TM is shown to have a high degree of interaction with six disciplines: Business and Management, Marketing, Economics, Planning and Development, Information Science, and Industrial Engineering and Operations Research. It is shown that visualizing and analyzing the TM network can provide an excellent overview of its multidisciplinary structure in terms of knowledge flow. This can help TM researchers easily grasp the historical development and fundamental features of TM.

**Keywords** Technology management · Multidisciplinary · Journal citation network · Brokerage analysis

## Introduction

Since the US government's 1987 publication on management of technology (US National Research Council 1987), technology management (TM) has expanded with great speed over the last two decades. Undoubtedly, TM has now become a self-sustained academic discipline (Pilkington and Teichert 2006). A large number of TM graduate programs

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H. Lee (✉)  
Department of Industrial and Systems Engineering, Seoul National University of Science and Technology, 172 Gongreung 2-dong, Nowon-gu, Seoul 139-746, Republic of Korea  
e-mail: hylee@seoultech.ac.kr

worldwide have been successfully launched and are being run in business and engineering schools (Nambisan and Wilemon 2003). Specialized professional organizations such as International Association for Management of Technology (IAMOT) and Portland International Center for Management of Engineering and Technology (PICMET), which were founded in the 1990s, have held annual conferences on TM.

In the meanwhile, over a dozen academic journals focused on TM have been disseminating knowledge on the field. The recent surge in TM research has resulted in many researchers scrutinizing TM literature. It is common practice for scholars to turn their attention toward the literature once a scientific discipline has reached a certain degree of maturity (Ramos-Rodríguez and Ruíz-Navarro 2004). Many attempts have been made to review the TM literature by using bibliometrics such as contents analysis and citation analysis. Some studies have investigated the characteristics of one particular TM specialty journal, including its historical developments, main themes, influential articles, and contributing authors and institutions. Examples include: *IEEE Transactions on Engineering Management* (Allen and Sosa 2004; Pilkington Pilkington 2007), *Technological Forecasting and Social Change* (Linstone 1999), *R&D Management* (Allen and George 1989; McMillan 2008), *Research Policy* (Callon et al. 1999), *Technovation* (Merino et al. 2006; Pilkington and Teichert 2006), and *Journal of Product Innovation Management* (Biemans et al. 2007; Durisin et al. 2010). Recent studies have broadened their coverage to include multiple TM specialty journals in order to explore the national characteristics and differences in research themes (Choi et al. 2012), research trends in developed and developing countries (Beyhan and Cetindamar 2011; Cetindamar et al. 2009), and the journal-wise characteristics of contributors (Ball and Rigby 2006). Another important research stream is to rank TM journals based on citation analysis. Cheng et al. (1999) developed the ranking of influential journals based on the citation information of top five TM specialty journals, and Linton and Thongpapanl (2004) extended the work by basing ten TM journals and employing additional measures of citation. The most up-to-date ranking of TM journals can be found in Thongpapanl (2012).

Although these studies have contributed to the body of TM research by capturing key trends and characteristics, there is one important feature of TM that has not been closely examined in previous studies, namely, its multidisciplinary nature. TM can be defined as a multidisciplinary field that, “links engineering, science, and management disciplines to plan, develop, and implement technological capabilities to shape and accomplish the strategic and operational objectives of an organization” (US National Research Council 1987). It is well-known that TM has an unusually high degree of interaction with other disciplines (Drejer 1997). Thus, scrutinizing the pattern and degree of the interaction of TM with its relevant disciplines is advantageous in grasping the historical development, fundamental features, and identity of TM. Nonetheless, the multidisciplinary nature of TM has been described and understood only in a subjective and qualitative manner. Very few efforts have been made to empirically and quantitatively measure the degree of interaction and strength of relationships between TM and other relevant disciplines.

In response, this study aims to reveal the multidisciplinary nature of TM by addressing the following two questions: (1) What disciplines have contributed to TM and to what disciplines TM has contributed? (2) What is the role of TM journals in promoting the exchange of knowledge with other disciplines? To answer these questions, the citation-based relationships between TM specialty and TM-related journals are analyzed by using social network analysis. Citation has been the most popular measure of direct relationships between academic journals (Calero Medina and van Leeuwen 2012; Pudovkin and Garfield 2002). Social network analysis has been employed frequently in conjunction with

bibliometrics, since it provides various measures to assess the academic relationships which can be best understood as a network (Otte and Rousseau 2002). In an effort to provide a quick and informative overview of an academic field, journal citation networks have been studied in many different fields (Ding et al. 2000; Leydesdorff 1994; McCain 1991; Reeves and Borgman 1983; Tsay et al. 2003; Zhou and Leydesdorff 2007). In particular, journal citation network analysis has been widely used to analyze various multidisciplinary fields (Leydesdorff 2007a; Rafols and Meyer 2010). This study also utilizes journal citation network analysis to grasp the multidisciplinary nature of TM. Network centrality metrics are employed to gauge the degree of contributions made by journals and disciplines in establishing the body of knowledge of TM. Brokerage analysis is utilized to identify the roles of TM specialty journals in disseminating the knowledge of TM.

The remainder of this paper is organized as follows. A review of the literature related to journal citation network analysis is presented in section “[Journal citation network analysis](#)”. Section “[Method](#)” explains the methods used in this study, and section “[TM journal network](#)” constructs and analyzes the TM journal network. The two research questions are addressed in section “[Multidisciplinary characteristics of TM](#)” by exploring the multidisciplinary nature of TM. Finally, the conclusions are provided in section “[Conclusions](#)”, along with directions for future research.

## **Journal citation network analysis**

Science can be considered a networked system of interconnected academic entities (e.g., fields, journals, authors, and articles) that produce and transfer knowledge (van Raan 2008). Therefore, the structure of a knowledge domain has often been described as a network in either a graphical or matrix form and analyzed from the network perspective based on graph theory. In this context, social network analysis, originally developed in social and behavioral sciences, has been employed frequently in conjunction with bibliometrics (Otte and Rousseau 2002). It provides a rich and systematic means of assessing networks by mapping and analyzing relationships among actors (Scott 1991). Basically, a network is composed of nodes (actors) and links (relationships). In bibliometrics, a node corresponds to an academic entity as a unit of analysis and an edge can be created through bibliometric indicators of relationships and similarities. The most common units in bibliometrics are words, documents, authors, and journals (Noyons 2001). Each unit represents different facets of a domain by constituting different levels of networks as a node (Börner et al. 2003). The link between those academic units can be built on the basis of commonly used bibliometric measures such as citation, co-citation, co-authorship, co-word, and co-classification (Noyons 2001; White and McCain 1997). Various types of networks can be constructed using different units of analysis and different types of indicators.

When it comes to the journal network, many researchers have employed journal network analysis to paint a picture of scientific knowledge at various levels of view such as a macro view of science (Bassecoulard and Zitt 1999), a meso view of a specific discipline (Ding et al. 2000; McCain 1991; Reeves and Borgman 1983), and a micro view of relevant journals related to a specific journal (Calero Medina and van Leeuwen 2012; Leydesdorff 2007b). In general, a journal network can be derived from either co-citation or citation analysis. In previous studies (Drejer 1997; McCain 1991, 1998; Tsay et al. 2003), co-citation analysis has often been utilized to construct a journal network. It is said that two

journals are co-cited when at least one article from each journal is listed in a citing article's reference list (McCain 1991). A high co-citation frequency between two journals implies a close linkage between them. However, similar to other co-occurrence measures, co-citation analysis can explain only similarity-based relationships, rather than direct influences. On the other hand, citation can capture the direct relationships between journals based on their actual influences. Citations are considered footprints that bear witness to the direction of knowledge transfer (King 1987). If a citation is made in a citing article to a cited article, it is assumed that the cited article has an influence on the citing article, which also implies that the researcher(s) or the journal of the cited article has an impact on the researcher(s) or the journal of the citing article. Thus, academic interrelationships between authors or journals can be determined based on citing-cited relationships between publications. Besides the simple count of citations received and made between journals, several measures that focus on the relationship between both citing and cited sides are available such as the relatedness index (Pudovkin and Garfield 2002) and the L-index (Calero Medina and van Leeuwen 2012). This study gauges the interrelationships between journals using the relatedness index, and its definition and operationalization will be provided in section "Method".

In sum, journal citation network analysis provides a quick and informative overview of an academic field as a form of a network composed of journals as nodes and citation-based relationships as links. Since the journal citation network can be practically utilized for researchers as well as librarians (Leydesdorff 2007a), journal citation network analysis has been conducted in many different fields such as economics (McCain 1991), mathematics (Zhou and Leydesdorff 2007), communications (Reeves and Borgman 1983), information science (Ding et al. 2000), medicine (Leydesdorff 1994), and semiconductors (Tsay et al. 2003). However, to my knowledge, no study has analyzed a journal citation network of TM. Although several studies have been conducted based on the citation analysis of TM specialty journals (Cheng et al. 1999; Linton and Thongpapanl 2004), they are centered on journal rankings based on forward citations made by TM journals, not on journal networks based on cross-citations.

Applying journal network analysis to the field of TM is even more important, since it has been considered a useful means for revealing the multidisciplinary nature of a journal or a field. As cross-disciplinary citation flows are considered an effective vehicle for analyzing interdisciplinary dynamics of science (van Leeuwen and Tijssen 2000), journal citation analysis has been a commonly used bibliometric technique for studying inter and multidisciplinary research (Calero Medina and van Leeuwen 2012; Rafols et al. 2012; van Raan and van Leeuwen 2002; Wagner et al. 2011). Various network metrics such as centrality are considered good indicators of inter- and multidisciplinary (Leydesdorff 2007a; Rafols and Meyer 2010). In this respect, journal citation network analysis has been applied to the examination of the convergence of disciplines or multidisciplinary fields such as information science and communication (Borgman and Rice 1992), chemical physics (Leydesdorff 1994), neural networks (McCain 1998), bionanoscience (Rafols and Meyer 2010), and nanotechnology (Leydesdorff and Zhou 2007).

## Method

### Journal selection

The first step is to select leading TM specialty journals as base journals. Identifying leading journals out of dozens of journals dealing with TM-related research is not an easy task, as

major journals of the field are not as apparent as those in established fields due to the high degree of existing multidisciplinary (Beyhan and Cetindamar 2011; Cheng et al. 1999; Linton and Thongpapanl 2004). Cheng et al. (1999) analyzed the top five journals identified in the study of Liker (1996). Linton and Thongpapanl (2004) selected the top eight journals uncovered in the study of Cheng et al. (1999), including four of the five base journals (except *The Journal of High Technology Management Research*), and added two more journals ranked above some of the base journals. The ten base journals used in Linton and Thongpapanl (2004) in alphabetical order are: *IEEE Transactions on Engineering Management (IEEM)*, *International Journal of Technology Management (ITJM)*, *Journal of Engineering and Technology Management (JETM)*, *Journal of Product Innovation Management (JPIM)*, *R&D Management (RDM)*, *Research Policy (RP)*, *Research-Technology Management (RTM)*, *Technological Analysis and Strategic Management (TASM)*, *Technological Forecasting and Social Change (TFSC)*, and *Technovation (TVN)*.

Although Ball and Rigby (2006) included *European Journal of Innovation Management* and *International Journal of Innovation Management* instead of *Technological Forecasting and Social Change* and Thongpapanl (2012) added five more journals (*Engineering Management Journal*, *Journal of Technology Transfer*, *Science and Public Policy*, *Industrial and Corporate Change*, *Industry and Innovation*), there seems to be agreement on the set of leading TM journals since the study of Linton and Thongpapanl (2004). The ten journals may not be an exhaustive set to use as a base to study the whole of TM literature, but most subsequent studies regarded the same set as leading TM specialty journals (Beyhan and Cetindamar 2011; Cetindamar et al. 2009; Choi et al. 2012; Linton and Embrechts 2007). I also prefer to rely on the ten journals as a base for this study. Table 1 lists the ten base journals along with their associated category information in Web of Science (WoS).

### Relationship measure

The next step is to select a measure of journal relationships. It is well-known that journal citation rates are highly subject to journal sizes (MacRoberts and MacRoberts 1996). Journal-to-journal citation rates have been studied for clustering of journals or delineation of specialty fields (Carpenter and Narin 1973; Leydesdorff 1994; Narin et al. 1972, 2000). However, these studies do not consider the varying sizes of journals. Pudovkin and Garfield (2002) proposed the relatedness index for measuring the relationship between journals by considering different journal sizes. The relatedness index is based on the rationale that the number of citations between two journals is proportional to the number of papers published in the cited journal and the number of references in the citing journals. It can be calculated as follows. Let the relatedness of journal  $i$  to journal  $j$  (or influence of journal  $j$  on journal  $i$ ) be  $R_{i>j}$ . Then,  $R_{i>j} = (H_{i>j} * 10^6) / (Pap_j * Ref_i)$ , where  $H_{i>j}$  is the number of citations in the current year from journal  $i$  to journal  $j$  (to papers published in all its years), and  $Pap_j$  and  $Ref_i$  are the number of papers published in journal  $j$  and the number of references cited in journal  $i$  in the current year, respectively. An arbitrary multiplier,  $10^6$ , is used to make the value of the relatedness index more easily perceived and handled. The relatedness factor, integrally characterizing the relatedness of a pair of journals, can then be defined as the larger of  $R_{i>j}$  and  $R_{j>i}$ .

Since the relatedness index is advantageous over simple citation rates in that it mirrors the size of journals, this study also adopts the relatedness index as a measure of journal relationships. It should be noted that the relatedness index, not the relatedness factor, is utilized in this study, because it does not aim to classify journals by their similarities, but to

**Table 1** List of ten base journals

Journal	Category in WoS		
	SSCI	SCI(E)	Number of assigned categories
IEEE Transactions on Engineering Management (IEEM)	Business/Management	Industrial Engineering	3
International Journal of Technology Management (IJTM)	Management	Multidisciplinary Engineering	2
Journal of Engineering and Technology Management (JETM)	Business/Management	Industrial Engineering/OR&MS	4
Journal of Product Innovation Management (JPIM)	Business/Management	Industrial Engineering	3
R&D Management (RDM)	Business/Management		2
Research Policy (RP)	Management/P&D		2
Research-Technology Management (RTM)	Business/Management	Industrial Engineering	2
Technological Analysis and Strategic Management (TASM)	Management		1
Technological Forecasting and Social Change (TFSC)	Business/P&D		2
Technovation (TVN)	Management	Industrial Engineering/OR&MS	3

*OR&MS* Operations Research & Management Science, *P&D* Planning & Development

measure directional relationships between journals. The value of the relatedness index for all journals included in WoS is available from the Journal Citation Report (JCR) published by Thomson Reuters.

## Network metrics

### *Centrality*

Centrality is a measure of the power of a node in a network, describing how close the node is to the center of a network. A variety of centrality measures are available, of which degree centrality, closeness centrality, and betweenness centrality, which were formalized by Freeman (1979), have been widely used. Degree centrality is defined as the number of nodes to which a given node is connected. In a directed network, this can be further divided into in-degree and out-degree centrality, that is, incoming and outgoing relations (Wasserman 1994). Relative degree centrality can be computed by dividing degree centrality by the highest possible degree,  $n-1$ , where  $n$  is the number of nodes in a network. Closeness centrality is based on the idea that nodes that are shorter in distance to other nodes are more central. It is defined as the inverse of the farness of a node which is the sum of distances from a given node to all other nodes. Two types of closeness centrality, namely, in-closeness and out-closeness, can also be computed for directed networks. Relative

closeness centrality is calculated as the product of closeness centrality and  $n-1$ . When it comes to betweenness centrality, it is assumed that a node is central if it lies on several shortest paths between other pairs of nodes. Betweenness centrality can be measured by summing the portion of shortest paths between two nodes through a given node for every pair of nodes. For a directed network, relative betweenness centrality is obtained by dividing betweenness centrality by the product of  $n-1$  and  $n-2$  (Gould 1987).

*Brokerage*

While centrality is a useful means for measuring the power or the influence of nodes, it cannot be used to identify the specific role of each node in a network. As a solution to this limitation, brokerage analysis has been developed in the context of exchange systems. The brokerage concept was proposed to explain the discrepancy between real power and centrality that had been observed in several empirical and simulation studies (Cook et al. 1983; Marsden 1983). Brokerage can be defined as a process “by which intermediary actors facilitate transactions between other actors lacking access to another,” (Marsden 1982). A brokered relation involves three actors, two of whom are the actual parties to the transaction, with the third being the broker.

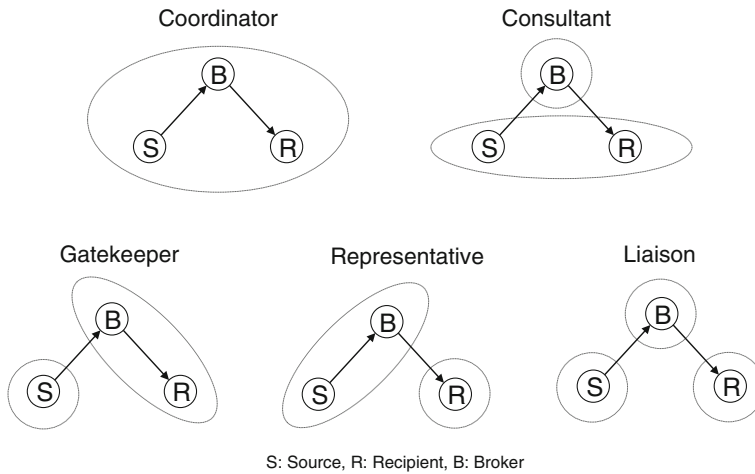
The types of brokers vary depending on the affiliations of actors between which a broker mediates when a network is partitioned into a set of mutually exclusive groups. Gould and Fernandez (1989) identified five structurally different types of brokers: coordinator ( $w_I$ ), consultant ( $w_O$ ), gatekeeper ( $b_{OI}$ ), representative ( $b_{IO}$ ), and liaisons ( $b_O$ ). Figure 1 provides a graphical representation of the five types of brokerage relations. The first two types are within-group brokerages. If all three nodes belong to the same group, the broker can be seen as a coordinator. In this study, if a TM specialty journal mediates between two other TM specialty journals, it is called a coordinator. The role of a consultant is similar to that of a coordinator, but the difference lies in the fact that the broker is affiliated with a different group. A TM specialty journal that links two non-TM specialty journals belonging to the same discipline can be considered a consultant. The last three types of brokers are between-group brokerages, and they can be differentiated by the group to which the broker belongs. When the broker belongs to the same group as the recipient node, it is labeled a gatekeeper. If a TM specialty journal delivers knowledge obtained from a non-TM specialty journal to another TM specialty journal, it acts as a gatekeeper. On the other hand, it is named a representative when the broker is affiliated to the same group as the source node. A TM specialty journal disseminating knowledge acquired from another TM specialty journal into a non-TM specialty journal can thus be seen as a representative. In the case of a liaison, all three nodes belong to different groups. When a TM specialty journal links two non-TM specialty journals from different disciplines, it plays the role of a liaison.

Brokerage analysis can be operationalized by measuring the raw scores for each type of brokerage roles. Let  $m_j$  denote the group of node  $j$  and  $N$  be the number of nodes in the network. A node  $j$ 's coordinator score,  $w_{Ij}$ , is defined as follows:

$$w_{Ij} = \sum_i^N \sum_k^N w_I(ik), (i \neq j \neq k) \tag{1}$$

where  $w_I(ik)$  equals 1 if  $ijk$  is true and if  $m_i = m_j = m_k$ , and 0 otherwise. In this way, the other types of brokerage scores can also be obtained: for consultant,  $w_O(ik) = 1$  if  $m_i = m_k \neq m_j$ ; for gatekeeper,  $b_{OI}(ik) = 1$  if  $m_i \neq m_j = m_k$ ; for, representative,





**Fig. 1** Five types of brokerage relations

$b_{IO}(ik) = 1$  if  $m_i = m_j \neq m_k$ ; for liaison  $b_O(ik) = 1$  if  $m_i \neq m_j \neq m_k$ . Moreover, node  $j$ 's partial scores for each type of brokerage can be computed by dividing the raw scores by  $g_{ik}$  where  $g_{ik}$  is the number of two-step paths between  $i$  and  $k$ . A node's total raw (or partial) brokerage score is equal to the sum of its five component scores. It should also be noted that the brokerage scores can be normalized by dividing the raw brokerage scores by the expected values derived from random assignment so that it can be used to compare the nodes from different groups with different number of members. However, this study does not require such normalization since the ten base journals belong to the same group, TM.

## TM journal network

### Network construction

For each of the ten base journals, all related journals and their relatedness indices were collected from the JCR. The period chosen for analysis was the most recent 5 years, from 2007 to 2011. As shown in Table 1, six out of the ten base journals are included in both the social science citation index (SSCI) and the science citation index (or expanded) (SCI(E)). The JCR also has two different versions for each edition, and each version of JCR provides the relatedness indices of related journals only included in each edition. Thus, both editions were considered and merged in generating the list of related journals for the six journals. Table 2 summarizes both total and average values of the relatedness index for both "citing" and "cited" along with the number of related journals.

The number of related journals varies across the ten base journals from 18 (*RTM*) to 213 (*RP*). Arranging overlapping journals produced a list of total 331 journals related to TM. To construct a complete network, lists of related journals for each of the 331 related journals need to be repetitively obtained, which may ultimately result in the whole set of journals being included in WoS. Considering indirect influences could enable an in-depth examination of journal-to-journal relationships, but it is likely to obstruct a clear understating of the knowledge domain. The scope of analysis is thus limited to direct



relationships in which the base journals are involved. Thus, the network is composed of only the journals that are directly connected to the base journals. For the same reason, the relationship between related journals is also neglected in the network, despite the availability of the relatedness index between them. The role of related journals in interfacing with TM and related disciplines is beyond the scope of this study. Thus, the resulting network can be viewed as a combination of the ten ego networks of the base journals.

The resulting data were reorganized into the form of an adjacency matrix, representing which journals are related to which other journals. The adjacency matrix ( $A$ ) is a valued  $341 \times 341$  matrix, which includes the ten TM specialty journals ( $S$ ) and the 331 TM-related journals ( $R$ ), where the entry  $a_{ij}$  is the relatedness index from journal  $i$  to journal  $j$ , that is,  $R_{i>j}$ . The adjacency matrix can also be divided into four matrix segments as follows:

$$\begin{array}{cc}
 & \begin{array}{cc} \text{TM specialty journals} & \text{TM-related journals} \end{array} \\
 \begin{array}{c} \text{TM specialty journals} \\ \text{TM-related journals} \end{array} & \left[ \begin{array}{cc} A_{SS} & A_{SR} \\ A_{RS} & 0 \end{array} \right] \quad (2)
 \end{array}$$

The matrix segment  $A_{SS}$  represents the interrelationship between the ten TM specialty journals.  $A_{SR}$  and  $A_{RS}$  involve the relatedness of TM specialty journals to TM-related journals and that of TM-related journals to TM specialty journals, respectively.  $A_{RR}$  is a zero matrix since the relatedness between TM-related journals is not considered, as mentioned before. Moreover, the diagonal entries in  $A_{SS}$  were replaced by zero, because the self-influence captured from self-citation is not important to this study.

Since the adjacency matrix is a valued one, it needs to be dichotomized for the sake of visualization and quantitative analysis. A binary transformation based on an exogenous, usually arbitrary, cut-off value is common in social network analysis, but it may lead to a significant amount of information loss. To determine the appropriate cut-off level, a sensitivity analysis was conducted with different threshold values of the relatedness index. A significant reduction in the number of nodes occurs between the threshold values of 30 and 60 and between 60 and 90, but no significant difference is observed between 90 and 120. A further analysis of centrality and brokerage for the cut-off value of 60, 90, and 120 produced similar results in terms of rankings and roles of the TM specialty journals. In this particular case, the cut-off value of 90, which leaves a total of 57 journals in the network, seems to be a reasonable cut-off value to generate the most visible and meaningful network. The adjacency matrix was therefore dichotomized by the cut-off value of 90 for visualization and for subsequent analysis. Excluding the journals isolated from the network at the given cut-off value yielded a  $57 \times 57$  matrix.

In visualizing a citation network, there are two options to depict directing arrows. When document A cites document B, the relationship can be represented by an arrow going from A to B, according to the direction of citation. On the other hand, the reverse arrow from B to A can be used if one intends to show the direction in terms of influence or knowledge flow. The citation relationship indicates that document B has an influence on document A or that a knowledge flow occurs from B to A. The latter approach is adopted because the role of journals in disseminating knowledge is of interest in this study. Conventionally, in a directed network, the source of the directed edge is a row, and the recipient is a column. Since the direction of influence is reverse in the current form of the dichotomized adjacency matrix, the matrix was transposed for the purposes of visualization.

**Table 2** Summary of relatedness index for ten base journals

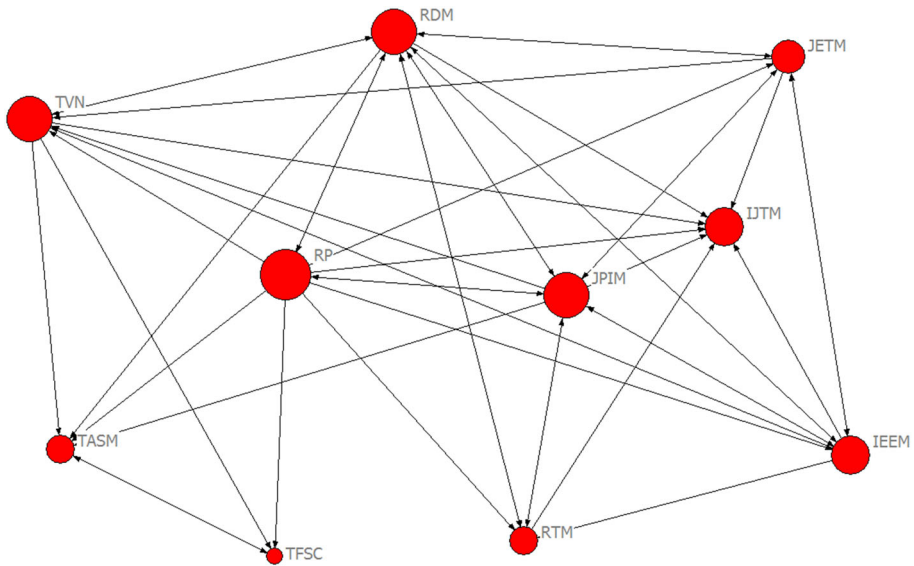
Journal	Number of related journals	Total relatedness		Average relatedness	
		Citing	Cited	Citing	Cited
IEEE Transactions on Engineering Management (IEEM)	120	6,369.7	4,637.5	53.1	38.6
International Journal of Technology Management (IJTM)	95	2,952.8	1,177.7	31.1	12.4
Journal of Engineering and Technology Management (JETM)	39	6,302.0	5,881.9	161.6	150.8
Journal of Product Innovation Management (JPIM)	98	8,970.5	8,683.8	91.5	88.6
R&D Management (RDM)	68	6,664.1	5,156.3	98.0	75.8
Research Policy (RP)	213	7,022.3	10,319.0	33.0	48.4
Research-Technology Management (RTM)	18	5,577.1	4,708.1	309.8	261.6
Technological Analysis and Strategic Management (TASM)	48	2,540.6	1,438.3	52.9	30.0
Technological Forecasting and Social Change (TFSC)	83	2,295.7	1,517.3	27.7	18.3
Technovation (TVN)	117	5,087.5	3,622.4	43.5	31.0
Average	89.9	5,378.2	4,714.2	90.2	75.6

### TM specialty network

Before analyzing the TM network composed of both TM specialty and TM-related journals, it will be interesting to explore the TM specialty network that includes only the ten base journals. The TM specialty network corresponds to the matrix segment,  $A_{SS}$ , in the transposed and dichotomized adjacency matrix. UCINET 6 was utilized to derive network metrics in conjunction with NetDraw for visualization. Figure 2 shows a visualization of the TM specialty network. The raw values of the relatedness indices between all of the ten base journals are positive, but applying the cut-off value led to a network centralization of 62.5 and 34.7 % in terms of out-degree and in-degree, respectively.

Table 3 summarizes the centrality values of the ten base journals along with their rankings in parentheses. *RP* is ranked the highest in terms of out-degree, followed by *JPIM* and *RDM*. The three journals also have a high level of betweenness centrality, together with *TVN*. When it comes to in-degree, *ITJM* and *RDM* are ranked the first and the second, respectively. No big difference is observed between degree and closeness centrality. The rankings in out-degree are the same as those in out-closeness. A notable difference is found between in-degree and in-closeness in the case of *TFSC*.

It is shown that the ten TM specialty journals have been actively exchanging knowledge with each other. In terms of the ratio of out-degree to in-degree, exactly half of the journals are above 1 while the other half are less than 1. Some prominent features can be found from the ratio of out-degree to in-degree and betweenness centrality. *RP* has an exceptionally high ratio of out-degree to in-degree (4.505); thus, it can be said that *RP* is playing the role of a knowledge supplier in the TM specialty network. All the other nine journals are influenced by *RP*, while only two journals, *RDM* and *JPIM*, have an influence on *RP*. On the other hand, *ITJM* is not drawn from any journal while it is influenced by all the



**Fig. 2** TM specialty network

other journals except *TFSC* and *TASM*. *ITJM* can be considered a pure customer in the network. *RDM* is ranked second for both in-degree and out-degree and has the highest ranking in terms of betweenness centrality. In other words, *RDM* has been the most active knowledge distributor in the field of TM. The role of the journals identified here is limited to the TM specialty network. What role the journals take in interacting with other disciplines is revealed hereafter.

TM aggregate network

The TM aggregate network is composed of the ten TM specialty journals and 47 TM-related journals. To grasp the multidisciplinary nature of TM and identify the role of the ten base journals in interacting with other disciplines, the 47 TM-related journals need to be assigned to relevant disciplines. The task is not easy because some of the related journals are multidisciplinary and can be classified into two or more disciplines. In fact, most of the journals are affiliated with two or more categories in WoS. However, brokerage analysis requires all nodes to be assigned to mutually exclusive groups. By referring to the aim and scope of the journals described in each journal’s homepage and by having a series of discussions with experts from various relevant disciplines, the 47 related journals were classified into six disciplines: Business and Management (BM), Marketing (MAR), Economics (ECO), Planning and Development (PD), Information Science (IS), and Industrial Engineering and Operations Research (IEOR). The disciplines are named on the basis of mainly the category titles defined in WoS, but some adjustments have been made by considering similarities between categories and the number of affiliated journals. Specifically, Economics, Planning and Development, and Information Science are ones of the subject categories in WoS. Industrial Engineering and Operations Research are separated in the WoS classification system, but many of their journals are co-classified into the two categories and thus they are merged. Business and Management are also merged although

**Table 3** Centrality of ten base journals in TM specialty network

Journal	Degree			Closeness			Betweenness
	Out	In	Ratio (out/in)	Out	In	Ratio (out/in)	
IEEE Transactions on Engineering Management (IEEM)	0.667 (4)	0.444 (6)	1.502 (3)	0.750 (4)	0.237 (7)	3.167 (4)	0.005 (6)
International Journal of Technology Management (IJTM)	0.000 (10)	0.778 (1)	0.000 (10)	0.100 (10)	0.333 (3)	0.300 (8)	0.000 (7)
Journal of Engineering and Technology Management (JETM)	0.556 (5)	0.444 (6)	1.252 (5)	0.692 (5)	0.237 (7)	2.923 (5)	0.000 (7)
Journal of Product Innovation Management (JPIM)	0.889 (2)	0.556 (3)	1.599 (2)	0.900 (2)	0.243 (5)	3.700 (2)	0.069 (2)
R&D Management (RDM)	0.889 (2)	0.667 (2)	1.333 (4)	0.900 (2)	0.250 (4)	3.600 (3)	0.139 (1)
Research Policy (RP)	1.000 (1)	0.222 (10)	4.505 (1)	1.000 (1)	0.225 (10)	4.444 (1)	0.014 (4)
Research-Technology Management (RTM)	0.333 (7)	0.444 (6)	0.750 (7)	0.563 (7)	0.237 (7)	2.375 (7)	0.000 (7)
Technological Analysis and Strategic Management (TASM)	0.111 (8)	0.556 (3)	0.200 (9)	0.111 (8)	0.429 (1)	0.259 (10)	0.014 (4)
Technological Forecasting and Social Change (TFSC)	0.111 (8)	0.333 (9)	0.333 (8)	0.111 (8)	0.375 (2)	0.296 (9)	0.000 (7)
Technovation (TVN)	0.444 (6)	0.556 (3)	0.799 (6)	0.643 (6)	0.243 (5)	2.643 (6)	0.051 (3)

they are separately dealt with in WoS. This is because most of the related journals that can be categorized as Management are also concurrently affiliated with Business in WoS. In the meanwhile, about half of the journals that can be classified as either Business or Management are marketing-centered ones. Thus, Marketing has been separated from Business and Management and constitutes an individual group. Table 4 shows the number of affiliated journals for each discipline. The list of the 47 related journals and their affiliated disciplines are given in “Appendix”. It should be noted that the number of affiliated journals in TM is 13. Three journals that were not initially included as base journals have been newly added to the TM category. They are *Innovation: Management, Policy & Practice, Journal of Technology Transfer*, and *Research Evaluation*.

Figure 3 provides a visual of the TM aggregate network composed of the 57 journals. TM specialty journals are placed at the center and surrounded by the related journals that are sectioned by their disciplines. The size of the nodes represents the degree centrality obtained by assuming that the network is undirected. It seems that the network captures the multidisciplinary nature of TM very well. It is shown that TM interacts highly with various disciplines. Moreover, which TM specialty journals are closely related to which disciplines can be easily understood.

To examine which TM specialty journals are important in the network, the values of centrality are first obtained and summarized as shown in Table 5. Some differences are

found when comparing the results within the TM specialty network. A remarkable change has occurred in the ranking of *JPIM*. It is ranked the highest in all of the five centrality measures except in-closeness. This is because all marketing journals included in the network are connected only to *JPIM*. The ranking of *RP* declined due to the rise of *JPIM*, but it is still ranked in the top 3 for all types of centrality. There is a considerable increase in its in-degree ranking from 10 to 3, which indicates that *RP* obtained more knowledge from other disciplines than from TM. *IEEM* has a high ranking for all types of centrality except out-closeness. This implies that it has been exchanging knowledge with other disciplines more actively than within TM. Slight change upwards or downwards in the ranking of other journals are also found. It should be noted that the number of base journals whose ratio of out-degree to in-degree is over 1 has decreased from five to one. *RP* is the only journal with a ratio  $>1$ . This implies that TM is acquiring more knowledge from other disciplines than it is providing. The knowledge flows in TM will be discussed further in section “[Contribution of related disciplines](#)”.

## Multidisciplinary characteristics of TM

### Contribution of related disciplines

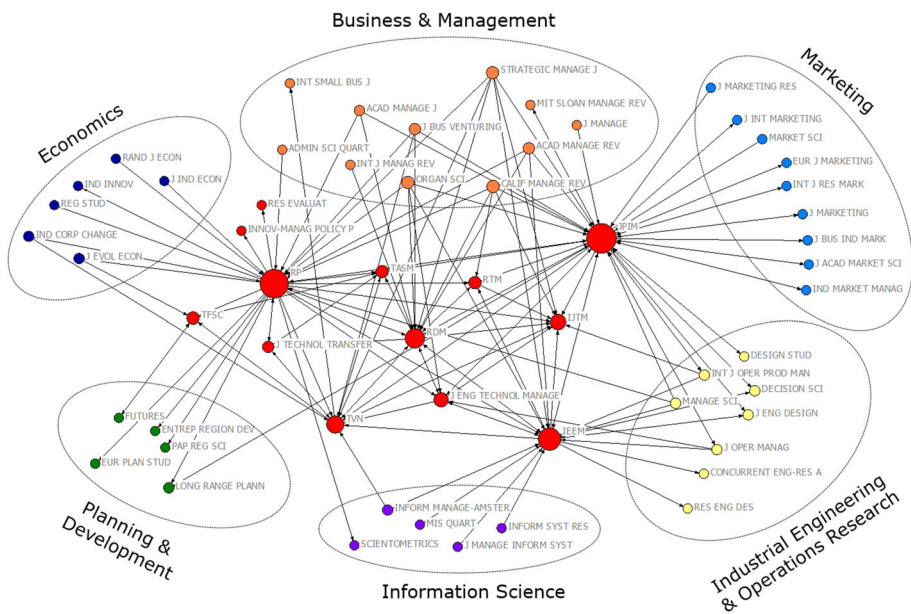
Visualization of the TM aggregate network enables us to quickly capture the whole picture of TM's connections to other disciplines, but concrete numbers may be helpful for a clearer understanding. Scrutinizing the TM aggregate network can reveal what disciplines have contributed to TM and what disciplines TM has contributed to. More specifically, the amount of contributions made between the related disciplines and the ten base journals is gauged based on knowledge flows identified in the TM aggregate network.

Table 6 presents the contribution rates of the six disciplines and TM to the ten base journals. The numbers indicate how many journals in each discipline have an influence on each base journal. The share of the ten base journals is also given in parentheses. Thus, it enables us to capture on which base journals each discipline has more or less impacts. First, the amount of contributions made by each discipline to the ten base journals can be found in the last row. A total of 116 incoming relations (the sum of the number of contributions in the last row) to the ten base journals exist, and exactly half of them come from TM itself, which can be evidence for the assertion that TM has now become a self-sustained discipline (Pilkington and Teichert 2006). For the other half, BM has the highest share with more than half (30 out of 58). The fact that BM is the highest contributing discipline to TM is not surprising. BM took the initiative in developing the field of TM, and all of the ten base journals are classified into either Business or Management, or both, in WoS. This also may be attributed to the finding in previous studies that TM researchers tend to publish their works in BM journals with high impact rather than in TM specialty journals (Cheng et al. 1999; Linton and Thongpapanl 2004; Thongpapanl 2012). The second influential discipline is IEOR. It is well-known that IEOR is the highest contributing discipline to TM in the engineering side, and many TM programs run in industrial engineering schools (Nambisan and Wilemon 2003). Moreover, four of the ten base journals are categorized into either Industrial Engineering or both Industrial Engineering and OR/MS in the SCI(E).

When it comes to journal-wise influences, the influence of Business and Management is relatively evenly distributed. All journals except for *TASM* and *TFSC* obtain knowledge from the discipline, but three journals, namely *JPIM*, *RDM*, and *RP*, share almost 70 % of its influence. *JPIM* is the only journal that is influenced by MAR. ECO affects *RP* fairly

**Table 4** Related disciplines and number of affiliated journals

Discipline	Number of affiliated journals
Technology Management (TM)	13
Business and Management (BM)	11
Marketing (MAR)	9
Economics (ECO)	6
Planning and Development (PD)	5
Information Science (IS)	5
Industrial Engineering and Operations Research (IEOR)	8
Total	57



**Fig. 3** TM aggregate network

significantly, and IS does *IEEM*. IEOR is heavily drawn from *IEEM* and *JPIM*. This is the expected result because the two journals are currently categorized into Industrial Engineering in WoS. On the contrary, *TVN* is not influenced by IEOR, although it is classified into Industrial Engineering as well.

From the reverse perspective, it might also worthwhile to examine which disciplines are more or less influenced by the ten base journals. Table 7 presents the contribution rates of the ten base journals to the six disciplines and TM. Examining the last row enables us to identify the degree of contribution made by TM to the other disciplines. Exactly two-thirds of outgoing relations from the ten TM specialty journals (60 out of 90) are distributed to TM. The main knowledge provider is *RP*, followed by *RDM* and *JPIM*, which was also found to be the case in the TM specialty network. *RP* has an influence on all the three

**Table 5** Centrality of ten base journals in TM aggregate network

Journal	Degree			Closeness			Betweenness		
	Out	In	Ratio(Out/In)	Out	In	Ratio(Out/In)	Out	In	Ratio(Out/In)
IEEE Transactions on Engineering Management (IEEM)	0.196 (3)	0.268 (2)	0.731 (4)	0.053 (4)	0.043 (5)	1.248 (5)	0.095 (3)		
International Journal of Technology Management (IJTM)	0.000 (10)	0.179 (5)	0.000 (10)	0.018 (10)	0.045 (3)	0.394 (8)	0.000 (9)		
Journal of Engineering and Technology Management (JETM)	0.089 (6)	0.107 (7)	0.832 (3)	0.053 (5)	0.043 (9)	1.250 (4)	0.001 (8)		
Journal of Product Innovation Management (JPIM)	0.393 (1)	0.393 (1)	1.000 (2)	0.055 (1)	0.043 (4)	1.267 (2)	0.235 (1)		
R&D Management (RDM)	0.161(4)	0.232 (4)	0.694 (5)	0.054 (3)	0.043 (6)	1.260 (3)	0.045 (4)		
Research Policy (RP)	0.375 (2)	0.250 (3)	1.500 (1)	0.055 (1)	0.043 (8)	1.280 (1)	0.169 (2)		
Research-Technology Management (RTM)	0.054 (7)	0.089 (9)	0.607 (6)	0.053 (6)	0.043 (10)	1.241 (6)	0.000 (9)		
Technological Analysis and Strategic Management (TASM)	0.018 (9)	0.107 (7)	0.168 (9)	0.018 (8)	0.051 (1)	0.357 (10)	0.003 (7)		
Technological Forecasting and Social Change (TFSC)	0.036 (8)	0.089 (9)	0.404 (8)	0.018 (8)	0.050 (2)	0.361 (9)	0.013 (6)		
Technovation (TVN)	0.107 (5)	0.179 (5)	0.598 (7)	0.052 (7)	0.043 (7)	1.228 (7)	0.027 (5)		



journals additionally classified under the TM category. Contrary to the previous result, which showed that BM has a high influence on TM, only two relations from TM (*JPIM* and *TVN*) to BM are found. This indicates that TM has yet to join the mainstream of BM. The most influenced discipline is IEOR, mainly from *IEEM* and *JPIM*. It is shown that *JETM* and *TVN* do not affect IEOR although they are affiliated with Industrial Engineering in WoS. As with the results in Table 7, *JPIM* is the only journal that has an influence on MAR. ECO and PD are affected mainly by *RP*.

Another important feature that can be derived from Tables 6 and 7 is the knowledge flows in TM. As mentioned before, the shares of TM and the other disciplines for incoming relations to TM are exactly equal. In other words, TM obtains knowledge equally from itself and from other disciplines. On the other hand, the number of outgoing relations from the TM specialty journals to other TM journals is twice as much as that to other disciplines. Put differently, the accumulated knowledge of TM is mainly consumed inside rather than outside. In addition, the ratio of incoming relations from other disciplines (58) to outgoing relations to them (30) is nearly double. Even though TM has become self-sustaining, it still seems to be on the consumer side in the macro knowledge domain. This may be due to its relatively short history when compared to other disciplines.

#### Brokerage roles of TM specialty journals

The roles of the ten TM specialty journals were revealed to some extent in the previous section, but this section is devoted to more closely identifying their roles in exchanging knowledge with other disciplines by using brokerage analysis. Table 8 summarizes the partial scores across the five brokerage types for the ten base journals in the weighted version. Two journals, *JPIM* and *RP*, have extremely high brokerage scores across all five types. *IEEM*, *RDM*, and *TVN* also take on the role of knowledge brokers. The brokerage roles of *JETM*, *TASM*, and *TFSC* are not significant, and *ITJM* and *RTM* do not mediate any discipline.

To specify the brokerage roles of the ten base journals, group-to-group brokerage maps of each journal are investigated and integrated into an aggregate form as shown in Table 9. Journals appearing in each cell are brokers who obtain knowledge from the discipline contained in the corresponding row and disseminate it to the discipline indicated in the column. No brokers exist for some cells, while other cells include up to three broker journals. The strength of brokerage relations is presented in parentheses, and insignificant relations whose raw score is  $<5$  are eliminated. The corresponding types of brokerage are also specified for each cell. According to the definition of the five types of brokerages, only one cell, the cell from TM to TM, corresponds to the coordinator. The cells in the first column and row are gatekeepers and representatives, respectively. The diagonal cells correspond to the consultant, and the remaining cells in the table are liaisons.

The results do not fall short of the expectations that one can have based on the classification of journals in WoS, but some interesting findings emerged from the brokerage analysis. All of the interactions of TM with MAR are made only by *JPIM*. When it comes to ECO and PD, *RP* is the only broker although *TFSC* is also one of the journals of P&D in WoS. Although all the ten base journals are categorized into either Business or Management in WoS, only *TVN* acts as a representative to BM, and *JPIM* is the only consultant to BM. Out of the four journals affiliated with Industrial Engineering, only two journals, *IEEM* and *JPIM*, highly mediate TM and IEOR. *IEEM* also plays the role of a gatekeeper from IS.

**Table 6** Contribution rates of related disciplines to ten base journals

Journal	TM	BM	MAR	ECO	PD	IS	IEOR
IEEE Transactions on Engineering Management (IEEM)	5 (8.6 %)	3 (10.0 %)				4 (80.0 %)	4 (36.4 %)
International Journal of Technology Management (IJTM)	8 (13.8 %)	2 (6.7 %)					1 (9.1 %)
Journal of Engineering and Technology Management (JETM)	5 (8.6 %)	1 (3.3 %)					1 (9.1 %)
Journal of Product Innovation Management (JPIM)	6 (10.3 %)	7 (23.3 %)	6 (100.0 %)				4 (36.4 %)
R&D Management (RDM)	7 (12.1 %)	7 (23.3 %)					
Research Policy (RP)	4 (6.9 %)	7 (23.3 %)		3 (60.0 %)			1 (9.1 %)
Research-Technology Management (RTM)	5 (8.6 %)	1 (3.3 %)					
Technological Analysis and Strategic Management (TASM)	7 (12.1 %)						
Technological Forecasting and Social Change (TFSC)	4 (6.9 %)			1 (20.0 %)	1 (100.0 %)		
Technovation (TVN)	7 (12.1 %)	2 (6.7 %)		1 (20.0 %)		1 (20.0 %)	
Total	58 (100 %)	30 (100 %)	6 (100 %)	5 (100 %)	1 (100 %)	5 (100 %)	11 (100 %)

**Table 7** Contribution rates of ten base journals to related disciplines

Journal	TM	BM	MAR	ECO	PD	IS	IEOR	Total
IEEE Transactions on Engineering Management (IEEM)	7 (58.3 %)					1 (8.3 %)	4 (33.3 %)	12 (100 %)
International Journal of Technology Management (IJTM)	1 (100.0 %)							1 (100 %)
Journal of Engineering and Technology Management (JETM)	6 (100.0 %)							6 (100 %)
Journal of Product Innovation Management (JPIM)	9 (39.1 %)	1 (4.3 %)	7 (30.4 %)		1 (4.3 %)		5 (21.7 %)	23 (100 %)
R&D Management (RDM)	10 (100.0 %)							10 (100 %)
Research Policy (RP)	13 (59.1 %)			4 (18.2 %)	4 (18.2 %)	1 (4.5 %)		22 (100 %)
Research-Technology Management (RTM)	4 (100.0 %)							4 (100 %)
Technological Analysis and Strategic Management (TASM)	2 (100.0 %)							2 (100 %)
Technological Forecasting and Social Change (TFSC)	2 (66.7 %)				1 (33.3 %)			3 (100 %)
Technovation (TVN)	6 (85.7 %)	1 (14.3 %)						7 (100 %)

**Table 8** Brokerage scores of ten base journals

Journal	Coordinator	Gatekeeper	Representative	Consultant	Liaison	Total
IEEE Transactions on Engineering Management (IEEM)	0.3	34.8	15.0	15.5	32.0	97.7
International Journal of Technology Management (IJTM)	–	–	–	–	–	0
Journal of Engineering and Technology Management (JETM)	–	1.4	–	–	–	1.4
Journal of Product Innovation Management (JPIM)	4.5	82.1	63.5	59.5	162.5	372.1
R&D Management (RDM)	11.3	19.6	0.0	0.0	0.0	30.9
Research Policy (RP)	12.3	78.2	25.5	11.0	83.5	210.6
Research-Technology Management (RTM)	–	–	–	–	–	0
Technological Analysis and Strategic Management (TASM)	1.0	–	–	–	–	1.0
Technological Forecasting and Social Change (TFSC)	–	2.0	3.0	0.0	1.0	6.0
Technovation (TVN)	6.0	8.9	6.0	2.0	2.0	24.9

**Conclusions**

This study investigated the multidisciplinary nature of TM using journal citation network analysis. The TM journal network was constructed based on the relatedness index between journals and analyzed by centrality and brokerage measures. The visualization of the TM network provided an excellent overview of TM as a multidisciplinary field in terms of knowledge flow. It was revealed that TM has close relationships with the six disciplines of BM, MAR, ECO, PD, IS, and IEOR. The roles of the TM specialty journals in linking TM with each of the disciplines were also identified by means of brokerage analysis.

TM has continued to evolve rapidly over the last two decades. For continuing advances in TM research, it is imperative to grasp the fundamental features of TM as a multidisciplinary field. In this respect, this study contributes to the field of TM by clarifying its identity by empirically and quantitatively capturing the relationships between TM and other relevant disciplines. The visualized and uncovered TM journal network can help prospective authors from relevant disciplines as well as TM researchers in selecting the proper outlets for their research and editors of TM specialty journals guide the editorial vision and direction.

This paper has some limitations that could serve as fruitful avenues for future research. Firstly, some of the related journals could be categorized into two or more disciplines, but they are assigned to only a single discipline because brokerage analysis requires partitioned groups to be mutually exclusive. If the affiliated discipline of a journal changes, its type of brokerage roles may also differ. Examining such changes for a specific journal of interest could provide richer implications about the role of journals in promoting the knowledge exchange. Secondly, the network construction was initiated by selecting the ten base

**Table 9** Brokerage roles of ten base journals

	TM	BM	MAR	ECO	PD	IS	IEOR
TM	[Coordinator] <i>RP</i> (12), <i>RDM</i> (11), <i>TVN</i> (6)	[Representative] <i>TVN</i> (6)	[Representative] <i>JPIM</i> (35)	[Representative] <i>RP</i> (12)	[Representative] <i>RP</i> (11)	[Representative] <i>JPIM</i> (20), <i>IEEM</i> (11)	
BM	[Gatekeeper] <i>RP</i> (40), <i>RDM</i> (20), <i>JPIM</i> (16)	[Consultant] <i>JPIM</i> (7)	[Liaison] <i>JPIM</i> (49)	[Liaison] <i>RP</i> (28)	[Liaison] <i>RP</i> (25)	[Liaison] <i>RP</i> (7)	[Liaison] <i>JPIM</i> (32), <i>IEEM</i> (9)
MAR	[Gatekeeper] <i>JPIM</i> (48)	[Liaison] <i>JPIM</i> (6)	[Consultant] <i>JPIM</i> (38)	[Liaison] <i>JPIM</i> (11)	[Liaison] <i>JPIM</i> (11)	[Liaison] <i>JPIM</i> (30)	
ECO	[Gatekeeper] <i>RP</i> (33)			[Consultant] <i>RP</i> (12)	[Liaison] <i>RP</i> (12)		
PD							
IS	[Gatekeeper] <i>IEEM</i> (22)						[Liaison] <i>IEEM</i> (16)
IEOR	[Gatekeeper] <i>JPIM</i> (18), <i>IEEM</i> (11), <i>RP</i> (6)		[Liaison] <i>JPIM</i> (28)				[Consultant] <i>JPIM</i> (15), <i>IEEM</i> (13)

journals based on the previous studies, but the relatedness analysis revealed that the three additional journals deserved to be included in the TM category. Including those journals from the beginning may produce somewhat different features of TM network. Thus, adopting an inductive approach to identifying the set of core TM journals can be another fruitful area of research. Thirdly, while this study did not consider the relationships between non-base journals, forming a full network that includes their interactions and compares their results may be interesting. In particular, measuring the eigenvector centrality of each journal in the full network is likely to reveal different aspects of journal importance. While the three measures of centrality used in this study are focused on direct influences, eigenvector centrality is related to indirect influences. The underlying idea of eigenvector centrality proposed by Bonacich (1972) is that a relationship with a more interconnected node contributes more to centrality than does a relationship with a less interconnected one. In other words, the centrality of a node is a function of the centrality of nodes that have relationships with the node (Bonacich and Lloyd 2001). This study does not measure eigenvector centrality since only the direct influences between the ten base journals and related journals are considered. Allowing for the relationships between TM-related journals makes indirect relationships evident where eigenvector centrality could be informative. Also, while this study adopted the relatedness index for measuring relationships between journals, it would be interesting to examine their relationships based on the raw citation matrix and compare the results. Moreover, since the data used in this study are limited to the citation relationships from the most recent 5 years, the TM network visualized in this paper is only a snapshot for that time period. Comparing the full picture of TM networks at different time periods may help to understand the evolutionary pattern of TM and predict its future trends.

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## Appendix

See Table 10.

**Table 10** List of 47 related journals

No	Journal	Abbreviation	Category
1	Academy of Management Journal	ACAD MANAGE J	BM
2	Academy of Management Review	ACAD MANAGE REV	BM
3	Administrative Science Quarterly	ADMIN SCI QUART	BM
4	California Management Review	CALIF MANAGE REV	BM
5	Concurrent Engineering-Research and Applications	CONCURRENT ENG-RES A	IEOR
6	Decision Sciences	DECISION SCI	IEOR
7	Design Studies	DESIGN STUD	IEOR
8	Entrepreneurship and Regional Development	ENTREP REGION DEV	PD
9	European Journal of Marketing	EUR J MARKETING	MAR
10	European Planning Studies	EUR PLAN STUD	PD
11	Futures	FUTURES	PD
12	Industrial and Corporate Change	IND CORP CHANGE	ECO

**Table 10** continued

No	Journal	Abbreviation	Category
13	Industry and Innovation	IND INNOV	ECO
14	Industrial Marketing Management	IND MARKET MANAG	MAR
15	Information and Management	INFORM MANAGE-AMSTER	IS
16	Information Systems Research	INFORM SYST RES	IS
17	Innovation-Management Policy and Practice	INNOV-MANAG POLICY P	TM
18	International Journal of Management Reviews	INT J MANAG REV	BM
19	International Journal of Operations and Production Management	INT J OPER PROD MAN	IEOR
20	International Journal of Research In Marketing	INT J RES MARK	MAR
21	International Small Business Journal	INT SMALL BUS J	BM
22	Journal of the Academy of Marketing Science	J ACAD MARKET SCI	MAR
23	Journal of Business and Industrial Marketing	J BUS IND MARK	MAR
24	Journal of Business Venturing	J BUS VENTURING	BM
25	Journal of Engineering Design	J ENG DESIGN	IEOR
26	Journal of Evolutionary Economics	J EVOL ECON	ECO
27	Journal of Industrial Economics	J IND ECON	ECO
28	Journal of International Marketing	J INT MARKETING	MAR
29	Journal of Management	J MANAGE	BM
30	Journal of Management Information Systems	J MANAGE INFORM SYST	IS
31	Journal of Marketing	J MARKETING	MAR
32	Journal of Marketing Research	J MARKETING RES	MAR
33	Journal of Operations Management	J OPER MANAG	IEOR
34	Journal of Technology Transfer	J TECHNOL TRANSFER	TM
35	Long Range Planning	LONG RANGE PLANN	PD
36	Management Science	MANAGE SCI	IEOR
37	Marketing Science	MARKET SCI	MAR
38	MIS Quarterly	MIS QUART	IS
39	MIT Sloan Management Review	MIT SLOAN MANAGE REV	BM
40	Organization Science	ORGAN SCI	BM
41	Papers In Regional Science	PAP REG SCI	PD
42	Rand Journal of Economics	Rand J ECON	ECO
43	Regional Studies	REG STUD	ECO
44	Research In Engineering Design	RES ENG DES	IEOR
45	Research Evaluation	RES EVALUAT	TM
46	Scientometrics	SCIENTOMETRICS	IS
47	Strategic Management Journal	STRATEGIC MANAGE J	BM

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