Coauthorship Networks: A Directed Network Approach Considering the Order and Number of Coauthors

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In many scientific fields, the order of coauthors on a paper conveys information about each individual’s contribution to a piece of joint work. We argue that in prior network analyses of coauthorship networks, the information on ordering has been insufficiently considered because ties between authors are typically symmetrized. This is basically the same as assuming that each coauthor has contributed equally to a paper. We introduce a solution to this problem by adopting a coauthorship credit allocation model proposed by Kim and Diesner (2014), which in its core conceptualizes coauthoring as a directed, weighted, and self-looped sociometric network. We test and validate our application of the adopted framework based on a sample data of 861 authors who have published in the journal Psychometrika. The results suggest that this novel sociometric approach can complement traditional measures based on undirected networks and expand insights into coauthoring patterns such as the hierarchy of collaboration among scholars. As another form of validation, we also show how our approach accurately detects prominent scholars in the Psychometric Society affiliated with the journal.

Introduction

The increase of coauthored research publications has led to a need for a better understanding of the fundamental principles of scientific collaboration (He, Ding, & Yan, 2012; Wray, 2002). The order of coauthors is one aspect of research on this broader topic that has particularly significant practical implications: Authorship information is used to assess scholars for employment, funding, and tenure. The underlying assumption here is that the order of coauthors implies information about the contribution of the involved individuals to a project and the credit they deserve for it (Beasley & Wright, 2003; Thomas et al., 2004). There is a large body of work on investigating and modeling the conventions for ordering coauthors across domains and on inferring the amount of each author’s contribution from the coauthor order (for a comprehensive review, see Marušić, Bošnjak, & Jerončić, 2011).

Although coauthorship has also been heavily studied by network scholars (Barabási et al., 2002; Goyal, van der Leij, & Moraga-Gonzalez, 2006; Moody, 2004; Newman, 2001), the ordering of coauthors has hardly been addressed from a network analytic perspective. In most coauthorship network studies, coauthoring relationships are conceptualized as undirected and binary (sometimes weighted) graphs (De Stefano, Giordano, & Vitale, 2011). Because ordering effects have not been considered in previous research, the implied assumption would be that coauthors contribute equally to a paper.

This procedure may conflict with the argument made by various scholars that to measure the impact of authors in an objective fashion their ordering needs to be considered (Jennings & El-adaway, 2012; Wren et al., 2007). In line with this thinking, we propose a method that accounts for author ordering with the ultimate goal of contributing to a more holistic understanding of the structure and implications of scholarly collaboration. In the following sections, we review previous coauthorship network studies in terms of coauthor order. Then we introduce a framework conceptualizing the coauthorship network as a directed, weighted, and self-looped sociometric graph, as proposed by Kim and Diesner (2014). We provide an empirical example to illustrate and evaluate the application of the proposed method. Finally, we discuss outcomes along with limitations and future directions.

Background

Coauthorship networks have been intensively studied in many fields, mainly with a focus on the macro-level properties of the networks. For example, multiple studies have confirmed the power-law distribution of the number of collaborators per author and the small-world structure of

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coauthor networks (Barabási et al., 2002; Liu, Bollen, Nelson, & Van de Sompel, 2005; Newman, 2004; Rodriguez & Pepe, 2008). Other studies identify actor-level characteristics such as the centrality of individual scholars (Ding, 2011; Yan & Ding, 2009). Both research traditions, however, have not paid much attention to the order of coauthors. One of the reasons for this might stem from a methodological convention (Faust, 1997): In coauthor networks, two authors are connected if they have worked together on a publication. Such a network can be represented as an adjacency matrix, where authors are denoted in the rows and publications in the columns. These two-mode or bipartite graphs are then usually folded into an author-by-author matrix for coauthorship network analysis. This method of network construction inevitably symmetrizes all relationships (Figure 1), where only the presence or absence of a relation matters (Barabási et al., 2002; Newman, 2001; Moody, 2004). Several scholars have attempted to advance this traditional approach. For example, some have assigned weights to undirected ties according to (a) the inverse of the number of authors per publication and (b) the cumulative frequency of collaboration between any pair of authors (De Stefano et al., 2011; Fiala, Rousselot, & Jezek, 2008; Newman, 2004; Sidiropoulos & Manolopoulos, 2006; Yan & Ding, 2011).

Others have turned to directed networks for developing sophisticated measures of author centrality. For example, Liu et al. (2005) modeled a directed coauthorship network by replacing all undirected relations with directed, reciprocated relations (Figure 2). Yoshikane, Nozawa, and Tsuji (2006) represented the order of coauthors as a directed network, where only the first author receives ties from coauthors (Figure 3).

Despite these advances, the common problem with most prior studies is that, given the symmetric nature or lack of hierarchies in coauthor relationships, ordering is not represented or considered. In the case of the directed network conceptualization by Liu et al. (2005), every pair of coauthors is connected via reciprocal ties. Even in Yoshikane et al.’s (2006) study, where the coauthor order is considered, coauthors except the first author are disconnected from each other, and their order is ignored.

The approaches discussed previously—except the one by Yoshikane et al. (2006)—are appropriate when applied to coauthorship networks where most of the coauthors are ordered alphabetically, which reflects equal contributions of all involved scholars, as often occurs in economics and mathematics (Endersby, 1996; Laband & Tollison, 2006; Riesenberg & Lundberg, 1990). The majority of scientific fields, however, have been reported to represent the coauthor order according to authors’ relative contribution (He et al., 2012; Spiegel & Keith-Spiegel, 1970; Wagner, Dodds, & Bundy, 1994; Waltman, 2012). Therefore, the aforementioned coauthorship network approaches, when applied to these fields, might cause a loss of information and lead to biased or false findings. We address these issues by adopting the method proposed by Kim and Diesner (2014) for modeling coauthorship networks that explicitly considers the order of coauthors. In the next section, we introduce this framework and explain how it overcomes the limitations of prior work on this topic.

**Methodology**

**Conceptualization of a Directed Coauthorship Network**

Synthesizing prior studies, we argue that the following three desiderata ought to be met to appropriately represent coauthor networks.

D1: All authors of a paper should be connected. This connectedness conveys the idea that authors are involved with one another in collaboration. Most previous coauthorship studies have assumed undirected connectedness among collaborators.

D2: Coauthor order should be explicitly represented in the network data. This desideratum is directly related to the...
hierarchical arrangement of coauthors: the first author should come before the second, the second before the third, and so on. D3: Each author’s individual contributions should be scaled by both her/his rank in the coauthor list and the number of authors on a publication. Although in some fields coauthors are acknowledged with the same maximum credit for a single piece of work, that is, one publication per each coauthor (Chan, Chen, & Cheng, 2009), it is common that authors are given less credits when the number of coauthors becomes larger (Newman, 2004; Wren et al., 2007).

To combine these three requirements, we turn to Kim and Diesner’s (2014) work, where coauthorship credit allocation is conceptualized by a directed network approach. Their network-based allocation (NBA) model of coauthorship credit is based on the following assumptions:

A1: Coauthors determine the order of coauthors according to their relative contribution to a paper. The amount of contribution decreases from the first to the last author.

A2: Each author is given an initial coauthorship credit that represents the unit value per publication divided by the number of coauthors. Here, each paper is assumed to have an equal value of one. This parameter setting is based on previous studies (Galam, 2011; Hagen, 2010; Vinkler, 1993).

A3: Coauthors of a paper distribute a certain proportion of their initial coauthorship credit in equal amounts to their preceding coauthors.

Building on these assumptions, NBA models scholarly coauthorship as an author transferring a part of his/her coauthorship credit to other authors as a sign of acknowledgement of their contribution. The application of this conceptualization to the three-coauthor case is shown in the sociometric digraph (Figure 4).

In the digraph, the respective order of authors is reflected by the number of incoming and outgoing ties (except for self-loops). Lead author A receives two ties from both authors B and C. Author B receives one tie from C while sending one to A. Author C sends two ties without receiving any tie. This inequality of exchange of directed ties generates a hierarchy between authors: author A precedes author B who is followed by author C in the coauthor list of a three-authored paper.

Each coauthor is given an initial coauthorship credit (IC), the paper value (assumed to be 1) divided by the number of collaborators (3 in Figure 4). Thus, the IC here is 1/3. After coauthors are given IC, they distribute a part of their IC (= transferable credit, TC) in equal portions to others preceding them in terms of the coauthor order while keeping the rest (= nontransferable credit, NC) to themselves. Thus, the initial coauthorship credit equals the sum of the transferable and the nontransferable credits (i.e., IC = TC + NC).

The TC is calculated by multiplying a distribution factor (d) to IC. Here, d can be any real number between zero and one, representing the ratio of IC that should be disseminated by each coauthor. In the example above, half of the authors’ ICs (d = 1/2 = 0.5) are distributed such that 1/6 (i.e., TC = 1/2 × 1/3) of each authors’ credit is transferred. Here, the last author C has to divide her/his TC into two portions (TC × 1/2 = 1/12) in order to equally distribute to author A and B, while s/he keeps the rest (i.e., NC = IC − TC = 1/3 − 1/6 = 1/6). The second author B transfers half of his/her IC (i.e., TC = 1/6) to the first author A and keeps the rest. Author A has no preceding author such that all of her/his TC is allocated to him/herself (the black, self-looped tie in Figure 4). S/he also keeps the NC. In the end, author A holds a total of 7/12 credits for the paper, author B holds 3/12, and author C has 1/6. Each author keeps the nontransferable credit (NC = 1/6) to themselves, which is depicted by a gray-colored, self-looped tie originating from each author and directed towards each node themselves in Figure 4. This relational allocation of authorship credit among coauthors can be generalized and applied to any multi-authored paper.

Noticeably, the adopted model produces different authorship credits even for the same paper, depending on the distribution factor (d), which equips the model with flexibility in allocating coauthorship credit scores. For example, the first author in a three-authored paper can receive a minimum credit of 0.33 (d = 0) and a maximum of 0.83 (d = 1) depending on d. Moreover, distribution factors can be assigned different values according to the number of coauthors. For instance, a two-authored paper can be modeled with a d different from that assigned to a three-authored paper. We refer readers to Kim and Diesner (2014) for a more detailed explanation of the NBA model.

So far, we have illustrated that ordered coauthor relationships can be conceptualized into a directed, weighted, and self-looped network. Such a conceptualization, that is, a directed, weighted coauthorship network, however, is not new. West, Jensen, Dandrea, Gordon, and Bergstrom (2013) modeled authors’ relationships through a directed, weighted network in citation analysis. Li and You (2013) conceptualized a directed, weighted, and self-looped coauthorship network where an author’s “energy” flows. But those models are different from the NBA model in that they...
still assume an equal contribution among coauthors. The uniqueness of the NBA model lies in that this conceptualization integrates the connectedness of coauthors, their order, the number of collaborators, and each author’s contribution into one framework, which together satisfy the desiderata proposed above. Here we extend the NBA model to coauthorship network analysis.

**Measures for Coauthorship Network**

The aforementioned conceptualization of coauthorship networks enables us to compute new metrics that supplement prior metrics used in previous coauthorship network studies. One primary use of network analysis in coauthorship research is the identification of prominent actors in the network. According to Knoke and Burt (1983) and Wasserman and Faust (1994), *prominence* is defined as a greater visibility of an actor when compared with others. They define two general types of prominence: centrality for symmetric (undirected) relations and prestige for asymmetric (directed) ones. Drawing on this categorization and the previous work applying centrality measures to coauthorship analysis (Liu et al., 2005; Yan & Ding, 2009; Yin, Kretschmer, Hanneman, & Liu, 2006), we apply four prominence measurements to the coauthorship network analyzed herein: degree, betweenness, and closeness centralities and indegree prestige, as defined in Table 1.

| Measure                | Formula                                                                 |
|------------------------|-------------------------------------------------------------------------|
| Degree Centrality      | $C_d(i) = \sum_{j \neq i} x_{ji}$                                       |
| Betweenness Centrality | $C_b(i) = \sum_{j \neq i} \frac{x_{ji}}{d(i, j)}$                       |
| Closeness Centrality   | $C_s(i) = \sum_{j \neq i} \frac{1}{d(i, j)}$                          |
| Indegree Prestige      | $P_i(i) = \sum_{j \neq i} x_{ji}$                                       |

TABLE 1. Overview of selected prominence measures (g is the total number of actors in a network).

Centrality is concerned with an actor’s relationships with others (Freeman, 1979; Wasserman & Faust, 1994). Specifically, in a coauthorship network the relation between a pair of actors represents the fact that these individuals are associated with each other through collaboration (Shumate et al., 2013). Directionality does not apply in this case. Thus, centrality measures have been defined and used mostly in coauthorship studies where undirected relations are assumed.

In an undirected, binary coauthorship network, degree centrality measures the number of unique coauthors that an author has with no sensitivity to the number of joint publications (Barabási et al., 2002; Moody, 2004; Newman, 2001). Here, an author is central when s/he has many collaborators. In an undirected coauthorship network, an author with high betweenness centrality has an advantage over others in terms of connecting diverse authors from different affiliations or domains, or controlling the flow of information on collaboration (Newman, 2001; Yan & Ding, 2009). As a distance-based measure like betweenness centrality, closeness centrality in a coauthoring relationship measures the extent to which an author can be easily connected to all the other authors in a network, and thus can mobilize the network without depending much on intermediary coauthors (Préll, 2012). One shortcoming of closeness centrality (Freeman, 1979) in this context is that it cannot be computed on a disconnected network, and most coauthorship networks are disconnected. To avoid this problem, this study calculates closeness centrality by summing the reciprocal distances between all actors (Borgatti, 2006).

Unlike centrality measures, prestige is mainly concerned with the direction of a relationship. Prestige refers to the extent to which an actor becomes a recipient or target of relations initialized by others in the network (Knoke & Burt, 1983). Specifically, an actor’s prestige in a network increases when s/he receives many nominations from other actors. Based on this line of argumentation, prestige cannot be measured in an undirected network (Wasserman & Faust, 1994). As shown in the conceptualization section, we model coauthorship networks as directed graphs, where an author transfers a portion of his/her coauthorship credit to her/his coauthors as an acknowledgment or endorsement of their contribution. This conceptualization necessitates a directed flow network instead of an undirected, representational coauthorship network (Shumate et al., 2013). Therefore, the coauthorship networks as modeled in this study can leverage existing prestige metrics, which has been inapplicable with previous undirected network approach.

An author in a directed coauthorship network is expected to receive more credits from coauthors when s/he relatively frequently appears in front in the coauthor order and/or when the number of collaborators is small. Thus, a prestigious author in terms of indegree prestige can be said to have led collaboration more often than other scholars and/or with a small number of collaborators per paper.

In the next section, a coauthorship network of scholars in a psychological journal is used to illustrate the application of conceptualization of directed coauthorship network. The selected set of prominence measures is used to produce rankings of authors. We compare the resulting rankings against each other as well as to real-world data on prominent scholars in the field related to the journal.
Analysis

Data Processing

In this section we report on the testing of the proposed solution in a real-world application setting. We compare our results to a proxy of ground truth—that is, expert verified data. For this purpose, we use a sample data set of coauthors who published in *Psychometrika*, one of the leading journals in quantitative psychology (Burgard, 2001). We obtained the data from two databases: PsycINFO and Scopus. PsycINFO has consistently maintained full names of authors, which helps disambiguate author names. Scopus logs the records of corresponding/reprint author. For querying these databases, we used “Psychometrika” as “Publication Name” and further constrained the search to “Article” as “Document Type.” We retrieved 1,263 (PsycINFO) and 1,208 (Scopus) articles published between 1980 and 2012. Both data sets were combined and de-duplicated, resulting in 1,161 unique articles. Among these articles, 498 articles (43%) had one author, whereas 663 articles (57%) were multi-authored. As we are interested in coauthoring relation, we analyzed the 663 multi-authored articles. Several authors used middle names or initials in some articles, but not in others. We manually disambiguated and consolidated names by leveraging affiliation or correspondence information provided in the articles as well as public information on these people. This reference resolution step identified 861 unique authors.

Our approach allows for unequal contributions of coauthors. In the field of psychology, authorship order reflects the relative magnitude of individual contribution (Maciejovsky, Budescu, & Ariely, 2008; Spiegel & Keith-Spiegel, 1970), with the first author typically having contributed the most (Maciejovsky et al., 2008). In some fields the last author is regarded as the senior author in charge of the paper. Scholars have reported different conventions on the last author’s contribution to joint work. Sometimes, the last author is viewed as contributing as much as the first author (Jian & Xiaoli, 2013). Other times, s/he is regarded as contributing less than the first author but more than the other coauthors (Retzer & Jurasinski, 2009; Tschannke, Hochberg, Rand, Resh, & Krauss, 2007). The contribution of the last author in the field of psychology is not reported on in prior scientometric research.

To address this limitation, we use the information about the corresponding author as a proxy for contribution (Milojević, 2012; Wren et al., 2007). Most journals require one of the coauthors to be identified as the corresponding author (or reprint author), who is usually regarded as a principal investigator, project leader, or mentor of graduate students (Jian & Xiaoli, 2013). The corresponding author is often considered the most important contributor to a collaborative project (Mattsson et al., 2011). In *Psychometrika*, 87.3% of 663 multi-authored papers list the first author as the reprint or corresponding author, whereas 10.2% specify the last author and 2.5% the middle authors. This empirical finding validates our conceptualization of the first author as the lead contributor. This decision is in sync with prior research in psychological scientometrics, which confirmed the same effect (Maciejovsky et al., 2008). Based on this rationale, we assume that the last author contributes the least when the first and corresponding authors are the same. In cases where the first and corresponding authors are different, we assume the corresponding author to be the lead contributor (Mattsson et al., 2011; Wren et al., 2007).1 We practically implement this choice by rearranging the list of authors: the corresponding author gets placed first, followed by the original first author and consecutively by all other coauthors.

Fitting Model to Empirical Data

Another issue that arises when applying the new model to coauthorship data is how to decide on the amount of coauthorship credit assigned to each author. Maciejovsky et al. (2008) analyzed the order of coauthors and the perceived contribution per author in a study with 52 professors and graduate students in psychology. Researchers presented the respondents with a total of 1,702 lists of coauthors of two-, three-, and four-coauthored (N) papers, and asked them to assign the amount of contribution (from 0% to 100%) to each coauthor according to their rank (r) in the coauthor order (Table 2). The outcome of this study was used as a proxy of ground-truth data to estimate the best distribution of contribution size of coauthors in *Psychometrika*.2

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1Although the last-positioned corresponding author is likely to contribute most to a paper in most cases, we cannot be absolutely sure for psychology due to the lack of research directly addressing the issue. Thus, we conducted a sensitivity test for three scenarios: the last-positioned corresponding author contributes (1) more than (2) less than and (3) equal to the first author. The indegree prestige rankings (Kendall’s tau rank order correlation) from these scenarios were highly correlated with one another (τ = 0.97–0.99, p < .01).

2Ideally, the ground-truth data would be a data set of contribution allocation directly assigned by authors of target papers. But it would be very difficult to invite all authors to report their contribution. Even if that is possible, authors in a paper might have different opinions on their contribution to a work (Shapiro, Wenger, & Shapiro, 1994). We use the perception of peer scholars, following previous studies on coauthorship credit allocation (Hagen, 2010; Maciejovsky et al., 2008; Wren et al., 2007). The overarching assumption of those studies is that coauthorship credit allocation is more of an issue to evaluators than to authors themselves: for example, peer scholars interested in the same field, journal editors, or committee members in charge of assessing scholars for inviting, hiring, promotion, tenure, or funding. Another assumption seems to be that the respondents of perceived coauthorship credit allocation studies were likely to be authors of their own papers in the past and, thus, their responses could be regarded as reflecting their evaluation of coauthoring experiences.
TABLE 3. The model’s coauthorship credit share fitted to empirical data from Maciejovsky et al. (2008).

| N    | 2      | 3      | ≥4     |
|------|--------|--------|--------|
| r    | 1      | 2      | 1      | 2      | 3      | 4      |
| Empirical Data | 0.61  | 0.39  | 0.49  | 0.29  | 0.22  | 0.42  | 0.24  | 0.19  | 0.14  |
| Model Score | 0.61  | 0.40  | 0.50  | 0.28  | 0.22  | 0.43  | 0.23  | 0.19  | 0.15  |
| d    | 0.21   | 0.33   | 0.39   |       |       |       |       |       |       |
| LOF  | 0.000001 | 0.000528 | 0.000297 |       |       |       |       |       |       |

In our model, the distribution factor \((d)\) affects the amount of contribution per author. To incorporate the coauthorship credit allocation information from Maciejovsky et al. (2008) into our study, we identified the distribution factor that best fits the empirical data. This was done by calculating the Lack of Fit (LOF) as a standardized deviation from model predictions as follows:

\[
LOF = \frac{1}{(n-1)} \sum \frac{(E-C)^2}{C} \tag{1}
\]

Here, \(n\) denotes the total number of empirical observations, \(E\) the empirical data based on the proxy of ground-truth data, and \(C\) the scores generated by our model. For example, to find the best fitting set of contribution scores from the model for the two coauthored case, the proxy of ground-truth values of 0.61 and 0.39 from the Maciejovsky et al. (2008) study were selected. Then those two values were compared to the scores obtained with our model run with various distribution factors ranging from 0.0 to 1.0. From the obtained results we selected the distribution factor with the lowest LOF value. Here, the lowest LOF represents the minimum error or difference between the proxy of ground-truth data and the model-generated scores. Our analyses show that the distribution factor of \(d=0.21\) best fits the proxy of ground-truth scores of two coauthors case, \(d=0.33\) the three coauthor case, and \(d=0.39\) the four coauthor case (Table 3). This implies that, as the distribution factor increases with the coauthor size, the coauthorship credit allocation is less equal in psychology, as more coauthors are involved.

The *Psychometrika* data include papers authored by 2 to 12 people, whereas the proxy of ground-truth data study only covers papers with two to four coauthors. Notably, papers written between two to four people constitute almost 99% of the data set. We decided to use the distribution factor for four coauthor case \((d=0.39)\) to the papers with more than four coauthors.

In Figure 5, the coauthorship credit shares generated by the model (with black-diamond points) are compared to those from the proxy of ground-truth empirical data (with gray-circle points, hard to see when the black and gray lines are on top of each other) for two to four coauthor cases (denoted by \(N\)). In that figure, the x-axes represent author ranks, and the y-axes represent coauthorship credit shares. According to the results, the model’s scores seem to be overall in close agreement with the proxy of ground-truth data. This also means that the model of our study generates a distribution of coauthorship scores that resemble it.

### Undirected Versus Directed Network Construction

To assess the performance of the proposed approach, we compared the obtained results to those from alternative prior approaches to analyzing coauthorship networks. The coauthorship network of *Psychometrika* was first generated as a directed, weighted, and self-looped network according to our conceptualization. Here, the weight of directed ties was assigned by the model to produce each author’s coauthorship credit share that best fits the proxy of ground-truth data from Maciejovsky et al. (2008). This network was used for calculating indegree prestige. Then the network was symmetrized as done in most previous studies. With this undirected network approach, the coauthor order is ignored. This undirected network was used for degree, betweenness, and closeness centrality measures.

### Results

#### Descriptive Statistics

Our study considered 861 unique authors in the *Psychometrika* coauthorship network (Table 4). A paper has on average 2.41 authors, and the average author collaborates with 2.52 other scholars. The graph is not connected: The largest component has 360 authors (42% of all coauthors), and the second largest one has 14 scholars. The overall density of the network is 0.003.

#### Rankings of Authors

Individual authors can be ranked according to different dimensions of prominence (Table 5). Each measure results in a different list, and each metric sheds light on a different aspect of scientific collaboration in these data.

To give a more detailed illustration, Table 6 shows the degree centrality and indegree prestige rankings for two authors who each wrote 11 articles. Although they have the same level of productivity in terms of number of papers published, they differ from a network analytical perspective. For example, according to the number of unique collaborators (degree centrality), Carroll ranks higher than Hwang because he has 13 unique coauthors, whereas Hwang has 12.

According to the indegree prestige measure, however, Hwang ranks higher than Carroll. The indegree measure favors an author who often leads coauthoring and/or publishes single papers with a small number of coauthors. As
shown in Table 7. Hwang served as the first author more often than did Carroll. The amount of coauthorship credits that Hwang received—according to the directed coauthorship network model of this study—is 4.96, whereas Carroll received 4.18.

Rank Order Correlation

As shown previously, each prominence measure ranks authors differently. For the macroscopic comparison of prominence metrics, we used Kendall’s tau (τ) rank order correlation. Kendall’s tau was chosen over Spearman’s rank order correlation because each measure produces many tied ranks, especially for mid- and low-ranked authors. Kendall’s tau is a nonparametric correlation measure which is useful when comparing data set with many tied ranks (Field, 2009). The rankings of the three prominence measures employed here were compared against each other (Table 8). In the comparison matrix, significance is signaled by “*” (at the .01 level, two-tailed), assigned to the right-upper side of each correlation coefficient value.

A noticeable feature here is the lack of dependency between indegree prestige and degree centrality (τ = .008, nonsignificant) and between prestige and closeness (τ = .037, nonsignificant). This shows that these measures capture different aspects of coauthoring in Psychometrika. Authors working with many collaborators are not necessarily those who collaborate more often or contribute more to collaboration than others. This might be partly due to the fact that degree centrality inflates the importance of an author if s/he participates in a paper with many coauthors. The betweenness centrality consistently shows an intermediate level of correlation with both degree (τ = .489) and indegree (τ = .517).

Hierarchy of Collaboration

The directed coauthorship network in this study is based on the hierarchical arrangement of coauthors per paper, from which we infer their relative contribution. To explore the overall hierarchical structure of coauthorship network in Psychometrika, authors were divided into three blocks according to the indegree prestige ranking: top 20% (Block1: rank 1 to 175), middle 30% (Block2: rank 176 to 432), and lower 50% (Block3: rank 433 to 861) groups. We have no theoretical grounds for grouping scholars in cases like our study. Therefore, we first divided authors in two groups: upper 50% and lower 50%. After that, we additionally divide the upper group into top 20% and the rest 30% because we might expect to see the so-called “20:80” distribution. Then their credit transfer was aggregated into the block level, and the coauthorship network was collapsed into a block matrix to represent the movement of credit between blocks (Table 9).

![FIG. 5. The model’s credit scores compared with empirical data for N-authored papers (x-axes: author ranks, y-axes: credit scores).](Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.)
In Table 9, blocks listed in the rows send credits to blocks in the columns. For example, the first row tells that Block1 sends credits to Block2 (8.72) and Block3 (2.43). The diagonal represents the transfer among within-block members. For example, in the first row a total of 349.24 credits are transferred among authors belonging to Block1. This table shows that 92% of credit transfer occurs in the diagonal.4 This is mainly due to the fact that the diagonal includes (a) the nontransferable credits assigned to each author before any transfer happens, which accounts for almost 75% of all credits (= = 496.59/663.00); (b) the self-allocated credits of first authors; and (c) the credits transferred among authors. To make the table more interpretable, these three types of credits in the diagonal need to be considered separately, as shown below.

First, Table 10 looks at transfer relationship from a different angle: Here, the nontransferable credits were removed from the diagonal of the credit mobility matrix. In the coauthorship network model of this paper, each author in a paper (a) receives an initial coauthorship credit (= the unit value of a paper divided by the number of coauthors), (b) distributes a part of the initial credit in equal amounts to other coauthors preceding him/her in coauthor order (= transferable credit

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**TABLE 5.** Top 20 authors per prominence measures.

| Rank | Centrality | Prestige |
|------|------------|----------|
| 1    | desarbo, wayne s. | desarbo, wayne s. | verhelst, norman d. | ten berge, jos m. |
| 2    | de boeck, paul | takane, yoshio | bentler, peter m. | bentler, peter m. |
| 3    | ten berge, jos m. | de leeuw, jan | heiser, willem j. | lee, sik-yum |
| 4    | takane, yoshio | ten berge, jos m. | de leeuw, jan | kiers, henk a. l. |
| 5    | bentler, peter m. | kiers, henk a. l. | takane, yoshio | desarbo, wayne s. |
| 6    | boker, steven m. | carroll, j. douglas | desarbo, wayne s. | yuan, ke-hai |
| 7    | carroll, j. douglas | bentler, peter m. | groenen, patrick j. f. | takane, yoshio |
| 8    | de leeuw, jan | mooijaart, ab | kiers, henk a. l. | brusco, michael j. |
| 9    | heiser, willem j. | hwang, heungsun | de boeck, paul | van mechelem, iven |
| 10   | kiers, henk a. l. | heiser, willem j. | ten berge, jos m. | de leeuw, jan |
| 11   | chow, sy-min | de soete, geert | van der heijden, peter g. m. | van der linden, wim j. |
| 12   | hwang, heungsun | groenen, patrick j. f. | de soete, geert | hwang, heungsun |
| 13   | lee, sik-yum | verhelst, norman d. | zhang, guangjian | carroll, j. douglas |
| 14   | sijtsma, klaas | kroonenberg, pieter m. | jennrich, roger i. | ceulemans, eva |
| 15   | van der linden, wim j. | young, forrest w. | mislevy, roger j. | meredith, william |
| 16   | van mechelem, iven | van der heijden, peter g. m. | yuan, ke-hai | heiser, willem j. |
| 17   | bates, timothy | de boeck, paul | chow, sy-min | böckenholt, ulf |
| 18   | brick, timothy | bekker, paul a. | mooijaart, ab | ramsay, james o. |
| 19   | estabrook, ryne | satorra, albert | zhang, zhiyong | sijtsma, klaas |
| 20   | fox, john | furnas, george w. | | |

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**TABLE 6.** An illustrated comparison of two prominence rankings of two authors.

| Measure | Carroll, J. Douglas | Hwang, Heungsun |
|---------|---------------------|-----------------|
| Number of papers | 11 | 11 |
| Degree ranking | 8 | 13.5 |
| Indegree ranking | 14 | 13 |

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**TABLE 7.** Coauthor lists of two authors (names in bold and coauthor names separated by semicolons).

Coauthor lists of papers J. Douglas Carroll participated in

- carroll, j. douglas; winsberg, suzanne
deo; geert; carroll, j. douglas;
arabie, phipps
takane, yoshio; carroll, j. douglas
desarbo, wayne s.; carroll, j. douglas;
arabie, phipps; carroll, j. douglas
carroll, j. douglas; pruzansky, sandra; kruskal, joseph h.
weinberg, sharon l.; carroll, j. douglas;
cohen, harvey s.
pruzansky, sandra; tversky, amos; carroll, j. douglas
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;
desarbo, wayne s.; carroll, j. douglas;

Coauthor lists of papers Heungsun Hwang participated in

- takane, yoshio; hwang, heungsun
hwang, heungsun; takane, yoshio
hwang, heungsun; takane, yoshio
hwang, heungsun; takane, yoshio
hwang, heungsun; dillon, william r.; takane, yoshio
hwang, heungsun; desarbo, wayne s.; takane, yoshio
hwang, heungsun; ho, moon-ho ringo; lee, jonathan
takane, yoshio; hwang, heungsun; abdi, herve
jung, kwanghee; takane, yoshio; hwang, heungsun; Woodward, todd s.
hwang, heungsun; suk, hye won; lee, jang-han; moskowitz, d. s.; lim, jooseop
TABLE 8. Kendall’s tau test between prominence measures.

| Degree | Betweenness | Closeness | Indegree |
|--------|-------------|-----------|----------|
| Degree | —           | .524*     | .489*    | .008     |
| Betweenness | —     | .346*     | .517*    |          |
| Closeness | —         | —         | .037     |          |
| Indegree | —           | —         | —        |          |

In the comparison matrix, significance is signaled by “*” (at the .01 level, two-tailed).

TABLE 9. Coauthorship credit transfer between blocks.

| Block1 | Block2 | Block3 |
|--------|--------|--------|
| Block1 | 349.24 | 8.72   | 2.43   |
| Block2 | 8.62   | 132.47 | 0.90   |
| Block3 | 18.38  | 16.35  | 125.88 |

TABLE 10. Coauthorship credit transfer with nontransferable credit excluded.

| Block1 | Block2 | Block3 |
|--------|--------|--------|
| Block1 | 76.45  | 8.72   | 2.43   |
| Block2 | 8.62   | 25.13  | 0.90   |
| Block3 | 18.38  | 16.35  | 9.43   |

TABLE 11. Coauthorship credit transfer with nontransferable credit excluded (normalized).

| Block1 | Block2 | Block3 |
|--------|--------|--------|
| Block1 | 0.4369 | 0.0498 | 0.0139 |
| Block2 | 0.0335 | 0.0978 | 0.0035 |
| Block3 | 0.0428 | 0.0381 | 0.0220 |

In other words, the top 20% of scholars did not obtain 80% of the credits. Instead, the differences between the sizes of self-allocated credit for first authors in each block are noticeable: An average of 0.2594 credits in Block1 was assigned by authors to themselves due to their role as the first author. This value is almost three times larger than the 0.0867 in Block2 and 56 times larger than the 0.0046 in Block3. Thus, we can say that, on average, authors in Block1 led collaboration as the first author much more often and/or with fewer collaborators than others in Block2 and 3. This also means that the first author role is not evenly assigned: A relatively small number of authors repeatedly take the lead in (small-sized) collaboration.

The flow of credits between blocks should also be highlighted. Scholars in Block3, who account for half (= 429) of 861 unique authors in this data set, transferred an average of 0.0428 credits to Block1 and 0.0318 to Block2. In contrast, the incoming transfer to Block 3 was 0.0139 from Block1 and 0.0035 from Block2. This asymmetric exchange of credits means that half the scholars (= Block3 = the lower 50%) participated in collaboration usually as secondary authors to those in the upper 50% (= Block1 and Block2).

Block1 authors transferred slightly more credits to Block2 authors (= 0.0498) than vice versa (Block2 gave 0.0335 to Block1). Block1 authors also supported Block3 authors as secondary authors, although the size of credits transferred by Block1 authors to Block3 authors (= 0.0139) is only 32% of the 0.0428 credits transferred by Block3 authors to Block1 authors. Meanwhile, Block2 authors received 0.0381 from Block3 authors and returned only 9% (= 0.0035). Thus, we can say that the top 175 authors in Psychometrika not only led coauthoring more often and also with fewer collaborators than others in Block2 and Block3 but also support collaboration as secondary authors than do Block2 authors.5

Another noticeable feature is that Block1 authors transfer more credits to their block members than to authors in other

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5This can be explained in another way. Authors might increase their indegree prestige by repeatedly collaborating with a small number of coauthors as lead authors or exchange the leading author role among them. Whether prestigious scholars collaborate with prestigious others or authors’ strategic collaboration makes them prestigious is a sociological issue beyond the scope of this study.
blocks. For example, authors in Block1 transferred an average 0.1775 credits ($= 0.4369 − 0.2594$) to within-block members, while they sent 0.0498 to Block2 members and 0.0139 to Block3 members. In other words, 74% of transferable credits (except the self-allocated credits for first authors) of Block1 members were exchanged among within-block members. In contrast, authors in Block 2 and Block3 transferred more to members outside their blocks than to within-block members. For example, Block2 authors transferred only 0.0111 ($= 0.0978 − 0.0867$) among within-block authors, whereas they sent 0.0370 ($= 0.0335 + 0.0035$) to authors in Block1 and 2. Block3 authors exchanged 0.0174 ($= 0.0220 − 0.0046$), whereas they sent 0.0809 ($= 0.0428 + 0.0381$) to out-block members. This implies that prestigious authors in terms of indegree supported prestigious colleagues by being their secondary authors.

By observing these credit transfers within and between blocks of authors, we can infer the hierarchy of collaboration in *Psychometrika*. Authors in each block show distinct patterns of collaboration. This illustrates that the newly introduced directed coauthorship network approach enables a more detailed interpretation of collaboration among scholars, which could be missed when solely relying on undirected networks.

**Structural Versus Real-World Prestige Validation**

Clearly, prestige measure in this study should not be regarded as a true reflection of real-world prestige. The conceptualization of prestige in this paper is defined in terms of ties received and is therefore purely based on network structure. This notion of structural prestige, like other centrality measures, can take on a different meaning from the notion that people have when they think of prestigious scholars in the actual world (de Nooy, Mrvar, & Batagelj, 2011; Knoke & Burt, 1983). To check the validity of new bibliometrics measures, several studies have validated their measures by comparing the results per measure against a pool of scholars assumed to be prominent, for example, membership in conference committees, editorial boards, and serving as keynote speakers in conferences (Liu et al., 2005).

We follow this strategy by comparing the results per measure against a pool of scholars assumed to be prominent in the Psychometric Society and its official journal *Psychometrika*. For this purpose, we selected scholars who have served as presidents of the society between 1991 and 2014 (elected), program committee members for the 2009–2013 period, trustees of the society from 2010, editorial council members from 2010, associate editors in 2013, and Lifetime Achievement Winners awarded by the society from 2008 to 2012. A total of 54 scholars’ names were collected. From this set we eliminated those who had not published in *Psychometrika*, which reduced the number of individuals to 41. We matched these 41 authors individually against the top 100 authors based on rankings results from centrality and prestige measures.

The results are shown in Figure 6. Among the top 100 authors ranked by the number of collaborators (degree), 19 of them also occur in the set of real-world prominent scholars. The betweenness centrality outperformed degree centrality by matching 25 prominent scholars. With indegree prestige ranking, 27 authors from that pool were represented. This indicates that, in the Psychometric Society and the *Psychometrika* journal, the indegree prestige measure reflects real-world prominent scholars as good as betweenness centrality or better than degree and closeness centralities.6

**Conclusion and Discussion**

In this paper, we applied the directed, weighted, and self-looped network model of coauthorship credit allocation proposed by Kim and Diesner (2014) to an analysis of a coauthorship network. This method enabled us to consider the coauthor order, which has not been fully conceptualized in previous coauthorship network research. Through the proposed model, coauthors are connected via directed relations based on transferring credits assigned to them according to the coauthor order and the number of collaborators per paper. This adopted approach allows us to use the indegree prestige measure, which was applied to a coauthorship network of the *Psychometrika* scholars for illustration of the measure’s usage. We showed that this measure can contribute to a deeper understanding of coauthoring patterns such as the hierarchical structure of collaboration. The validity of

6A paired-samples *t*-test was conducted to evaluate the difference between indegree prestige ($M = 17.91, SD = 8.31$) and betweenness centrality ($M = 17.09, SD = 7.38$) in detecting prominent scholars. The difference was statistically significant, *t* (99) = 6.04, *p* < .0005 (two-tailed). The mean difference was .82 with a 95% confidence interval ranging from .55 to 1.09. The eta squared statistic, 0.27, indicated a large effect size. Therefore, we can say that indegree prestige performs better than degree centrality. This test was the idea of an anonymous reviewer.
the proposed measure was also tested against a real-world group of prominent scholars in the considered field and compared with other centrality measures.

This study has limitations related to the data and methodology. We used real-world data from *Psychometrika*. This decision was based on our belief that this particular journal could serve as a good example, mainly because it is an outlet for high-quality research in the field of psychology where coauthor ordering conventions and perceived authorship credit allocation have been well studied. The findings from this study, however, should not be generalized to other journals in psychology or to other fields without empirical validation.

Another limitation is that most scholars publish in more than one journal. Thus, the analysis of a single journal would show an incomplete map of collaborative activities among scholars. This might explain why some prominent scholars in terms of presidential leadership, committee, and editor membership did not appear in *Psychometrika* or were not ranked highly based on the four prominence metrics. Analogously, additional prominent scholars might not have been detected because they usually publish as a single author, a group which was excluded from this study.

In addition, it is undeniable that the pool of scholars used for validation purposes might not be representative. Because there is no widely agreed-on definition or ranking of prominence, a biased decision is inevitable. For example, if the program committee members of the Psychometric Society before 2009 were included, the result of matching real-world prominent scholars and structurally prominent ones might be different.

Most important, several assumptions of the new model are open to challenge. The structural prestige constructed through a directed coauthorship network is based on the perception of readers of research products, not on the actual contribution of coauthors. Moreover, the coauthorship credit shares assigned to an author based on the order and number of coauthors can only approximate the empirical data. As the model is not flexible enough to represent every possible authorship credit distribution, it is quite possible that a difference between the empirical data and the fitted model scores can exist.

Despite the outlined limitations, this study is meaningful in that the proposed conceptualization gets closer to revealing diverse aspects of coauthor relationship. For example, by relaxing the assumption that each paper is assigned an equal value, we can assign the number of citations to each paper and, thus, integrate coauthor order and citation in coauthorship network analysis. In addition, single-authored papers, which have been excluded in traditional coauthorship studies, can be considered for scholarly impact, as the model can conceptualize them as self-looped networks.

Furthermore, based on the directed network approach, coauthorship can be studied with other previously well-defined network analysis techniques such as position and role, hierarchical clustering, and network topology. We hope this study will encourage other researchers to develop more refined and sophisticated methods and investigate diverse research questions on scholarly collaboration using the directed coauthorship network concept.

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