Formulating Closeness Centralities on Workflow-supported Performer-Activity Affiliation Networks

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***Abstract*—This paper focuses on a special type of enterprise social networks, which is called 'workflow-supported activity-performer affiliation network,' and particularly formulates a metric of closeness centrality to numerically analyze the degree of clerical familiarities among performers who are involved in a workflow-supported activity-performer affiliation network. A workflow model specifies enactment sequences of the associated activities and their affiliated relationships with roles, performers, invoked-applications, and relevant data. These affiliated relationships can be revived into valuable organizational knowledge supporting business intelligence as well as managerial decision-making activities. In this paper, we particularly focus on formulating the affiliated relationships between activities and performers in a workflow model to numerically measure the closeness centralities of performers as well as the closeness centralities of activities. We also devise a series of algorithms for implementing the formulated closeness centrality equations, and describe the ultimate implications of these closeness centrality formulations in workflow-supported organizations.**

***Keywords*-workflow-supported affiliation network, ICN-based workflow model, organizational closeness centrality, business process intelligence**

I. Introduction

In recent, the workflow literature starts being interested in re-positioning the traditional workflow systems into the tools of business and organizational knowledge and intelligence. It begins from the strong belief that social relationships and collaborative behaviors among workflow-performers obviously affect the overall performance and being crowned with great successes in the real businesses and the working productivity as well. The typical pioneering outcomes of those re-positioning works ought to be [1][2][3], in which the authors formalize mechanisms and their related algorithms to discover workflow-supported social networking knowledge from workflow models and their enactment event logs. In general, the workflow model is formally defined by using the information control net (ICN)[4] methodology. In defining a workflow model, we have to specify four types of the performer-centered affiliation relationships[5] by associating each individual performer with all the essential entity-types such as activity, role, application, and relevant data. The Fig. 1 illustrates these performer-centered affiliation relationships in a specific ICN-based workflow model. We are particularly interested in the performer-activity affiliation relationships in a workflow model, where the performers (or actors) are linked in activities through joint participations; reversely, the activities are connected to performers through joint involvements; the authors' research group has modeled a collection of these participations and involvements as "*workflow-supported performer-activity affiliation network model*[6][7]."

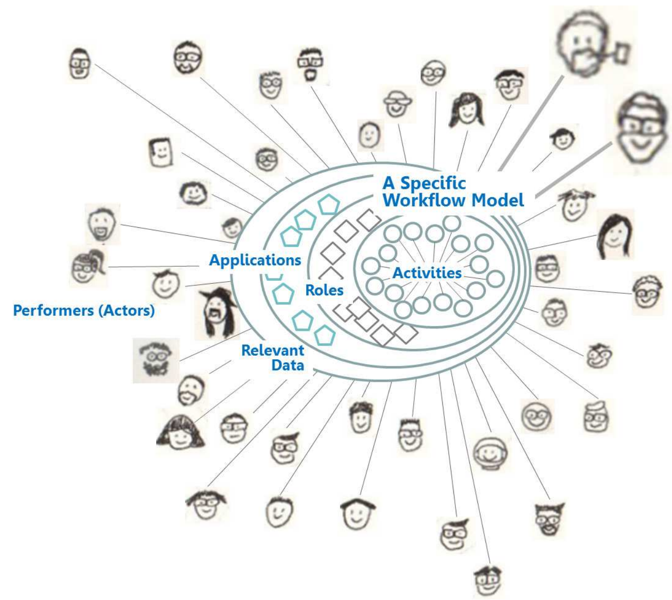

Fig. 1. Four Types of the Performer-Centered Affiliation Relationships in an Information Control Net of Workflow Model

In this paper, we focus on quantitatively measuring the degree of performers' familiarity by adopting the concept of closeness centralities into the workflow-supported performer-

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activity affiliation network model. We assume that a workflow-supported performer-activity affiliation network is formed by two key groups of the entity types such as a set of performers and a collection of activities in a corresponding information control net of workflow model. That is, we are basically concerned about numerically formalizing the closeness centralities among the performers involved in fulfilling the ICN-based workflow model. Basically, the affilation network is coming from the formal properties[8]—two-mode and non-dyadic networks—of affiliation relationships. Since the workflow-supported performer-acitivity affiliation network is a two-mode network, the complete measurements should be done by giving centrality indices for both performers and activities. Generally, there are four centrality analysis techniques, such as degree, closeness, betweenness, and eigenvector centralities, and we particularly measure the closeness centralities of performers and the closeness centralities of activities in this paper.

By analyzing the closeness centralities on a workflow-supported performer-activity affiliation network formed from a set of activity-performer affiliated relationships in an ICN-based workflow model, it is eventually possible to visualize and numerically express how much the performers and the activities are interrelated and collaboratively closed in enacting the corresponding workflow model. As a consequence, the main purpose of this paper is to theoretically develop formulations and their algorithms for calculating the closeness centralities for activities and performers in a 'workflow-supported performer-activity affiliation network. In the next section, we simply describe the basic concept of the workflow-supported performer-activity affiliation network through the formal definition and the graphical representation as well. And, in the consecutive section we try to formulate the closeness centrality equations and their implementation algorithms with an operational example. Finally, we finalize the paper with describing a couple of related works in the last section.

II. Workflow-Supported Performer-Activity Affiliation Network Model

In order to represent the workflow-supported performer-activity affiliation knowledge, [6] has recently defined a graphical (Bipartite Graph) and formal representation model, which is dubbed workflow-supported performer-activity affiliation network model, which is abbreviated to APANM, and it has two types of nodes—a set of performers and a set of activities—and a set of relationships between those nodal types. Thus a workflow-supported performer-activity affiliation network model is a two-mode network model with aiming to accomplish the following dual objectives:

- to uncover the relational structures of workflow-performers through their joint involvement in activities, and
- to reveal the relational structures of workflow-activities through their joint participation of common performers.

Additionally, those relational structures can be weighed to measure the extent of their strengths by assigning a value to each of relations between nodal types. Therefore, there are two types of performer-activity affiliation networks—binary performer-activity affiliation network and valued performer-activity affiliation network. In the binary performer-activity affiliation network, its value (0 or 1) implies a binary relationship of involvement (or participation), while values in the valued performer-activity affiliation network may represent various implications according to their application domains; typical examples of values might be stochastic (or probabilistic) values, strengths, and frequencies. The formal knowledge representation of workflow-supported performer-activity affiliation network model is defined in the following [Definition 1][6].

[Definition 1] Workflow-Supported Performer-Activity Affiliation Network Model. A workflow-supported performer-activity affiliation network model is formally defined as $\Lambda = (\sigma, \psi, \mathbf{S})$, over a set $\mathbf{C}$ of performers (actors), a set $\mathbf{A}$ of activities, a set $\mathbf{V}$ of weight-values, a set $\mathbf{E}_p \subseteq (\mathbf{C} \times \mathbf{A})$ of edges (pairs of performers and activities), and a set $\mathbf{E}_a \subseteq (\mathbf{A} \times \mathbf{C})$ of edges (pairs of activities and performers), where, $\wp(\mathbf{A})$ represents a power set of the activity set, $\mathbf{A}$:

- $\mathbf{S}$ is a finite set of work-sharing actors or groups of some external performer-activity affiliation network models;
- $\sigma = \sigma_p \cup \sigma_v$ /* Involvement Knowledge */
  where, $\sigma_p : \mathbf{C} \longrightarrow \wp(\mathbf{A})$ is a single-valued mapping function from a performer to its set of involved activities; $\sigma_v : \mathbf{E}_p \longrightarrow \mathbf{V}$ is a single-valued mapping function from an edge $(\in \mathbf{E}_p)$ to its weight-value;
- $\psi = \psi_a \cup \psi_v$ /* Participation Knowledge */
  where, $\psi_a : \mathbf{A} \longrightarrow \wp(\mathbf{C})$ is a single-valued mapping function from an activity to a set of participated performers; and $\psi_v : \mathbf{E}_a \longrightarrow \mathbf{V}$ is a single-valued function from an edge $(\in \mathbf{E}_a)$ to its weight-value;

Furthermore, the affiliation knowledge representation can be graphically depicted by an affiliation graph. So, a workflow-supported performer-activity affiliation network's graphical model consists of two types of graphical nodes—a set of performers (shaped in hexagon) and a set of workflow activities (shaped in circle)—and a set of non-directed edges between two nodal types, which means that a workflow affiliation network is a non-directed graph. That is, in a workflow-supported performer-activity affiliation graph, non-directed lines connect performers aligned on one side of the diagram to the workflow activities aligned on the other side. Importantly, a performer-activity affiliation graph does not permit lines among the performers nor among the workflow activities. Therefore, a performer-activity affiliation graph with g performers and h workflow activities can be transformed into a matrix with 2-dimension of $g \times h$.

III. Closeness Centrality Measurement Formulations

In general, an affiliation networking graph[9] is a bipartite graph, as described in the previous section, in which non-directed lines connect performers aligned on one side of the diagram to the workflow activities aligned on the other side.

Based upon the performer-activity affiliation networking graph and its affiliation matrix, it is possible to analyze a variety of knowledge analytics issues[9], such as mean rates analysis[8], density measurements[8], and centrality measurements[9], raised from the social networking literature. In this paper, our focus concentrates upon the centrality measurements of the workflow-supported affiliation network model. More precisely speaking, we try to propose an algorithmic formalism for analyzing organizational centrality measurements, particularly closeness centrality measurements, of a workflow-supported performer-activity affiliation network.

A. Definition of Affiliation Matrix

Eventually, it is necessary for the performer-activity affiliation network model to be analyzed in a mathematical representation. A workflow-supported performer-activity affiliation network model is graphically represented by a bipartite graph, and at the same time it is mathematically represented by an affiliation matrix. The affiliation matrix can be realized by either an involvement matrix or a participation matrix. That is, a performer-activity affiliation network model is mathematically transformed into an activity-performer affiliation matrix that records the presence and absence of g performers at h workflow activities; thus its dimensions are g rows and h columns, respectively. If a certain performer ϕ_i attends a workflow activity α_j, then the entry in the i^{th} and j^{th} cell in the matrix equals to 1; otherwise the entry is 0. Denoting a binary activity-performer affiliation matrix as $\mathbf{Z}$, its $x_{i,j}$ values meet these conditions:

$$x_{i,j} = \begin{cases} \mathbf{1} & \textit{if performer}, \phi_i, \textit{is affiliated with activity}, \alpha_j \\ \mathbf{0} & \textit{otherwise} \end{cases} \tag{1}$$

- The row total, also called row marginals, ($\overline{D}_r$), of a performer-activity affiliation matrix $\mathbf{Z}$ sum to the number of workflow activities that each performer will attend, which implies the involvement relations between activities and performers in a specific workflow model.

$$\overline{D}_r = \left[\sum_{j=1}^{h} x_{i,j} \right]_{i=1}^{g} \tag{2}$$

- The column marginals, ($\overline{D}_c$), indicate the number of performers who will attend each workflow activity's enactment, which implies the participation relations between performers and activities in a corresponding workflow model.

$$\overline{D}_c = \left[\sum_{i=1}^{g} x_{i,j} \right]_{j=1}^{h} \tag{3}$$

Also, assuming an affiliation networking graph has g performers and h activities, then its bipartite affiliation matrix has dimensions $(g + h) \times (g + h)$. Consequently, using the involvement affiliation matrix ($\mathbf{Z}_p$) and the participation affiliation matrix ($\mathbf{Z}_a$) forms an affiliation bipartite matrix, $\mathbf{X}^{P,A}$, which can be schematically represented as the following equations, (4) and (5).

$$\mathbf{X}^{P,A} = \begin{bmatrix} \mathbf{0} & \mathbf{Z}_p \\ \mathbf{Z}_a & \mathbf{0} \end{bmatrix} \tag{4}$$

$$\mathbf{X^P} = \mathbf{Z_p} \cdot \mathbf{Z_a} \qquad \mathbf{X^A} = \mathbf{Z_a} \cdot \mathbf{Z_p}; \tag{5}$$

B. Closeness Centrality Formulations

[8] gives a series of well-described equations that can be applied to calculating the closeness centralities based upon the bipartite matrix of a workflow-supported performer-activity affiliation network model. Before we develop an algorithm of the closeness centrality measurements in the next subsection, we need to restate those closeness centrality equations, and consider the relationship between the closeness centrality of a performer and the closeness centrality of the activities to which the performer belongs, and the relationship between the closeness centrality of an activity and the closeness centrality of its performers.

Basically, the meaning of closeness centrality index in a social network[1][3] implies the average geodesic distance that a node is from all other nodes in the graph. In other words, it is to calculate the 'farness' of a node from other nodes in the graph. As described in the previous section, the performer-activity affiliation network is a special type of social network, and it is represented by a bipartite graph with relationships (or connections) between performers and activities. Thus, calculating the geodesic distances in a bipartite graph begins with a function of the distances from the activities to the performers which each of them belongs. The distance from a node i representing a performer to any node j (either performer or activity) is $d(i, j) = 1 + \min\{d(k, j)\}_k$, for every activity node k adjacent to i. Given this properties, the closeness centrality of a performer in the bipartite graph can be expressed with a function of the distances from the performer's activities, k:

$$\sum_{j=1}^{g+h} d(i,j) = \sum_{j=1}^{g+h} \left[1 + \min\{d(k,j)\}_k\right], i \neq j \tag{6}$$

1) Closeness Centrality of Performers: Based on the distance function of (6), the following expressions are the index and the standardized index of the closeness centrality of a performer with a function of the minimum geodesic distances from its activities to other actors and to other activities, respectively. Note that every activity n_a is adjacent to performer n_i.

- The Index of Closeness Centrality of Performers

$$OC_C(n_i) = \left[\sum_{j=1}^{g+h} d(i,j) \right]^{-1} \quad (i \neq j) \tag{7}$$

$$OC_C(n_i) = \left[1 + \sum_{j=1}^{g+h} \min\{d(n_a, n_j)\}_a \right]^{-1} \quad (i \neq j) \tag{8}$$

- The Normalized Index of Closeness Centrality of Performers

$$OC_C^S(n_i) = (g + h - 1) \cdot [OC_C(n_i)] \tag{9}$$

$$OC_C^S(n_i) = \left[1 + \frac{\sum_{j=1}^{g+h} \min\{d(n_a, n_j)\}_a}{g+h-1} \right]^{-1} \quad (i \neq j) \tag{10}$$

2) Closeness Centrality of Activities: By revising the distance function of (6), it is also necessary to make the expressions for the index and the standardized index of the closeness centrality of an activity with a function of the minimum geodesic distances from its performers to other activities and to other performers. Note that every performer m_p is adjacent to activity m_j.

- The Index of Closeness Centrality of Activities

$$OC_C(m_i) = \left[1 + \sum_{j=1}^{g+h} \min\{d(m_p, m_j)\}_p \right]^{-1} \quad (i \neq j) \tag{11}$$

- The Normalized Index of Closeness Centrality of Activities

$$OC_C^S(m_i) = \left[1 + \frac{\sum_{j=1}^{g+h} \min\{d(m_p, m_j)\}_p}{g+h-1} \right]^{-1} \quad (i \neq j) \tag{12}$$

Summarily speaking, the equations (9) and (12) are for normalizing the index of closeness centrality by multiplying by $(g+h-1)$. Suppose that a performer is close to all others, which means that its adjacent activity has a direct tie to every performer in the bipartite graph. Thus the computed index values will be vary according to their graph sizes. In order to control the size of the graph, it is necessary for the individual index to be normalized so as to allow meaningful comparisons of performers across different graphs. This explanation can be identically applied to the normalized index for activities.

C. Algorithms of the Geodesic Distances

Based upon those closeness centrality equations, we develop a series of algorithms for calculating the closeness centralities of all the performers as well as all the activities associated with a workflows-supported performer-activity affiliation network. The following subsections concisely describe the details of the algorithms and their explanations. Note that we won't put all the algorithms that are needed to calculate the closeness centralities.

1) Algorithm of the geodesic distances for performers: By extensively applying the equations of (8) and (10), we can calculate the closeness centralities of performers for a workflow-supported performer-activity affiliation network. The essential part of those equations must be the functions of calculating the geodesic distance from a performer node, n_i, to another performer node, n_j, and the geodesic distance, which implies the shorted path, from a performer node, n_i, to an activity node, m_j, respectively. In this subsection, we devise an algorithm with recursive functions, to algorithmically implement the essential equations. Assume that the algorithm operates on a given performer-activity affiliation adjacency matrix, $\mathbf{X}^{P,A}$, representing the corresponding workflow-supported performer-activity affiliation network, and its functional procedure name is 'PcGeodesicDistance()' using two recursive functions, 'gDistance()' and 'hDistance()', which are calculating the geodesic distances from a specified performer (n_i) to all the performers and to all the activities, respectively. The output of the algorithm is the geodesic distance of a performer, n_i, to either a performer or an activity, n_j, and it is saved on the performer-centered geodesic distance matrix, $\mathbf{G}^{P,A}$, as a value of the cell, $\mathbf{G}^{P,A}[n_i, n_j]$. The time complexity of the algorithm is $\mathbf{O}(\mathsf{N})$, where $\mathsf{N} = g+h-1$, and g is the number of performers and h is the number of activities in a corresponding workflow-supported performer-activity affiliation network.

The Geodesic Distances Algorithm for Performers:

Given Global A Binary Affiliation Bipartite Matrix, $X^{P,A}[g+h, g+h]$;
Given Global A Set of Performers, **P**;
Given Global A Set of Activities, **A**;

Procedure Name: PcGeodesicDistance
Input A Performer (From), n_i;
Either a Performer or an Activity (To), n_j;
Output A Performer-Centered Geodesic Distance Measure, $G^{P,A}[n_i, n_j]$;

Local An Activity Distance Vector, $G_k[1..h]$, initialized by **maximum**;
Local A Performer Distance Vector, $H_k[1..g]$, initialized by **maximum**;

Begin Procedure
  If ($n_j \in \mathbf{P} \wedge n_i \neq n_j$)
    For ($\forall m_k \in \boldsymbol{A}_k$ *adjacent to* n_i)
      $G_k[m_k] \leftarrow$ **gDistance**(n_i, m_k, n_j);
    roF
    $G^{P,A}[n_i, n_j] \leftarrow 1 +$ **minimum**$\left(G_k[i] \right)_{i=1}^{h}$;
  Else If ($n_j \in \mathbf{A}$)
   For ($\forall m_k \in \boldsymbol{A}_k$ *adjacent to* n_i)
     If ($m_k = n_j$)
       $G_k[m_k] \leftarrow 0$; **break**;
     Else If ($m_k \neq n_j$)
       $\mathbf{P}_s \leftarrow$ all performers who are adjacent to m_k;
       $\mathbf{P}_s \leftarrow \mathbf{P}_s - n_i$;
       For ($\forall n_s \in \boldsymbol{P}_s$)
         $H_k[n_s] \leftarrow$ **hDistance**(m_k, n_s, n_j);
       roF
       $G_k[m_k] \leftarrow 1 +$ **minimum**$\left(H_k[i] \right)_{i=1}^{g}$;
       Initialize $H_k[1..g]$ by **maximum**;
   roF
   $G^{P,A}[n_i, n_j] \leftarrow 1 +$ **minimum**$\left(G_k[i] \right)_{i=1}^{h}$;
  Return $G^{P,A}[n_i, n_j]$;
End Procedure

2) Algorithm of the Geodesic Distance for Activities: We develop an algorithm for implementing the above equations of (11) and (12) by revising the algorithm developed in the previous subsection. By using the algorithm we are able to calculate the closeness centralities from a activities' point of view. Likewise, the essential part of those equations must be the functions of calculating the geodesic distance from an activity node, m_i, to another activity node, m_j, and the geodesic distance from an activity node, m_i, to a performer node, n_j, respectively. Assume that the algorithm also operates on a given performer-activity affiliation adjacency matrix, $\mathbf{X}^{P,A}$, representing the corresponding workflow-supported performer-activity affiliation network, and its functional procedure name is 'AcGeodesicDistance()' using two recursive functions, 'gDistance()' and 'hDistance()', too. The output of the algorithm is the geodesic distance measure of an activity, m_i, to either a performer or an activity, m_j, and it is saved on the activity-centered geodesic distance matrix, $\mathbf{G}^{P,A}$, as a value of the cell, $\mathbf{G}^{A,P}[m_i, m_j]$. The time complexity of the algorithm is $\mathsf{O}(\mathsf{N})$, where $\mathsf{N} = g + h - 1$, and g is the number of performers and h is the number of activities in a corresponding workflow-supported performer-activity affiliation network.

The Geodesic Distances Algorithm for Activities:

Given Global A Binary Affiliation Bipartite Matrix, $X^{P,A}[g + h, g + h]$;
Given Global A Set of Performers, **P**;
Given Global A Set of Activities, **A**;

Procedure Name: AcGeodesicDistance
Input An Activity (From), m_i;
    Either an Activity or a Performer (To), m_j;
Output An Activity-Centered Geodesic Distance Measure, $G^{A,P}[m_i, m_j]$;

Local A Performer Distance Vector, $H_k[1..g]$, initialized by **maximum**;
Local An Activity Distance Vector, $G_k[1..h]$, initialized by **maximum**;

Begin Procedure
    If ($m_j \in \mathbf{A} \wedge m_i \neq m_j$)
        For ($\forall n_k \in \boldsymbol{P}_k$ *adjacent to* m_i)
            $H_k[n_k] \leftarrow$ **hDistance**(m_i, n_k, m_j);
        roF
        $G^{A,P}[m_i, m_j] \leftarrow 1 +$ **minimum**$\Big(H_k[i]\Big)_{i=1}^{g}$;
    Else If ($m_j \in \mathbf{P}$)
      For ($\forall n_k \in \boldsymbol{P}_k$ *adjacent to* m_i)
    If ($n_k = m_j$)
            $H_k[n_k] \leftarrow 0$; **break**;
          Else If ($n_k \neq m_j$)
            $\mathbf{A}_s \leftarrow$ all activities that are adjacent to n_k;
            $\mathbf{A}_s \leftarrow \mathbf{A}_s - m_i$;
            For ($\forall m_s \in \boldsymbol{A}_s$ *adjacent to* n_k)
              $G_k[m_s] \leftarrow$ **gDistance**(n_k, m_s, m_j);
            roF
            $H_k[n_k] \leftarrow 1 +$ **minimum**$\Big(G_k[i]\Big)_{i=1}^{h}$;
            Initialize $G_k[1..h]$ by **maximum**;
      roF
      $G^{A,P}[m_i, m_j] \leftarrow 1 +$ **minimum**$\Big(H_k[i]\Big)_{i=1}^{g}$;
    Return $G^{A,P}[m_i, m_j]$;
End Procedure

D. Implications of the Closeness Centralities

In this paper, we are particularly interested in adopting the concept of closeness centrality to measure *the degree of familiarity* among performers in a workflow-supported organization. The semantic significance of closeness distance in terms of the familiarity metric refers to how quickly a performer can interact with others via intermediary activities where the performers are jointly participating to. In consequence of those consecutive calculations of all the performers, we can draw the answers to the following question from measuring the closeness centralities on a workflow-supported performer-activity affiliation network:

- **The degree of familiarity**: How quickly can a performer interact with others *via* very few intermediary activities in enacting workflow procedures?

Conclusively, the answer to the question is able to convey a very valuable and meaningful insight to the corresponding workflow-supported organization. We assure that the primary rationale of the closeness centrality ought to be on the question and the answer. We strongly believe that a series of theoretical formulations on the closeness centralities and their implementable algorithms devised in this paper can be used in developing a workflow-supported organizational intelligent system supporting to measure the individual levels as well as the group levels of the closeness centralities in a workflow-supported organization.

IV. Related Works

Recently, technology-supported social networks and organizational behavioral analytics issues have been raised in the IT literature. Naturally, the workflow literature has just started transitioning into and focusing on social and collaborative work analyses in workflow-supported organizations, because workflow management systems are "human systems," where workflow procedures must be designed, deployed, and understood within their social and organizational contexts. It is quite natural for the concept of enterprise social networks (workflow-supported affiliation networks) to be raised and issued from these human-centered organizational contexts. It is important to remind that the human-centered affiliation relationships reveal how each of the individuals is associated with the essential entity-types of the organizational resources like activity, role, application, and relevant data. Particularly, in this paper we focus on the Performer-Activity affiliation networking knowledge[7] and fomulate their equations for calculating the closeness centralities among the performers.

K. P. Kim [7] firstly issued the workflow-supported performer-activity affiliation network as a special type of organizational social network knowledge acquired from deploying workflow technologies. In the paper, the author theoretically derived a series of concepts and algorithms not only for representing and discovering those knowledge but also for analyzing the discovered knowledge. Battsetseg, *et al.* [10] proposed a theoretical formalism to analyze a workflow-supported performer-activity affiliation network by measuring the organizational closeness centralities of performers as well as the organizational closeness centralities of activities. Note that we try to extend the proposed theoretical formalisms through this paper. H. Kim, *et al.* [11] formalized the workflow-supported performer-role affiliation network. In the paper, the authors formally defined the workflow-supported performer-role affiliation networking knowledge through a series of theoretical formalisms and practical implementation for modeling, discovering, and visualizing workflow performer-role affiliation networking knowledge. H. A. Reijers, *et al.* [12] pioneered the human-centered resource management issue in a workflow-suppoted organization, which can be interpreted by a conceptual species of the workflow-supported affiliation networks. Through this research, they showed that the high degree of geographical closenesses among workflow-performers be leaded to the posivitve effect on workflow-supported organizational performance by conducting a case study of distributed teamworks on a workflow process model.

Conclusively, we would say that these pioneering works, until now, concerning about the human-centered affiliation knowledge are the outputs in the stage of initiative research works, which is the discovery phase. The next stage ought to be the analysis phase. The paper of [10] was just a halffinished step forward to the analysis phase shifting from the discovery phase. In particulay, P. Busch and his colleague in [13][14] raised the logical necessity of the conceptual triangulation of workflow management, social network analysis, and knowledge management, which ought to be one of the circumstantial evidences of the theoretical importance of this paper.

V. Conclusion

In this paper, we have formulated a series of closeness centrality measurement equations and proposed their related algorithms and descriptions for analyzing a workflow-supported performer-activity affiliation network representing involvement and participation behaviors between workflow-based people and workflow-based activities. We have introduced the basic concept of workflow-supported performer-activity affiliation network and its implications as a meaningful mechanism of organizational knowledge and intelligence. Particularly, we restate the mathematical equations for the closeness centrality measurements, and develop an functional algorithm for implementing those closeness centrality equations. As a future work, we have a plan to implement those concept and algorithms for measuring the closeness centralities as a fundamental function of the organizational knowledge and intelligent management system.

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