A Theoretical Framework for Closeness Centralization Measurements in a Workflow-Supported Organization

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Abstract

In this paper, we build a theoretical framework for quantitatively measuring and graphically representing the degrees of closeness centralization among performers assigned to enact a workflow procedure. The degree of closeness centralization of a workflow-performer reflects how near the performer is to the other performers in enacting a corresponding workflow model designed for workflow-supported organizational operations. The proposed framework comprises three procedural phases and four functional transformations, such as discovery, analysis, and quantitation phases, which carry out ICN-to-WsoN, WsoN-to-SocioMatrix, SocioMatrix-to-DistanceMatrix, and DistanceMatrix-to-CCV transformations. We develop a series of algorithmic formalisms for the procedural phases and their transformative functionalities, and verify the proposed framework through an operational example. Finally, we expatiate on the functional expansion of the closeness centralization formulas so as for the theoretical framework to handle a group of workflow procedures (or a workflow package) with organization-wide workflow-performers.

Keywords: workflow-supported org-social network (WsoN), information control net (ICN), closeness centralization measures/vector (CCV), workflow model, organizational knowledge management, workflow intelligence

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1. Introduction

The workflow model is concretized through multiple-level abstraction [1], such as view, conceptual, and physical levels of abstraction, to provide a series of theoretical bases for designing and implementing a workflow management system. The typical view-level abstract is the information control net [2], which is a formal way of specifying a workflow procedure particularly focusing on the control flow aspect of activities. The conceptual-level abstract is a various formation of transformations according to the essential aspects of the workflow procedure like performer-dependency, control-dependency, role-dependency, and data-dependency aspects. The physical-level abstract of a workflow procedure represents the architectural distribution of its activities in realizing a workflow management system. The scope of this paper conceives a series of theoretical formalisms related with conceptual-level abstract of the workflow model, particularly focusing on the performer-dependency aspect. Recently, workflow modeling techniques [1], organizational intelligence techniques [3, 4], and social network analysis techniques [5] are converging on "workflow-supported people," which starts from the strong belief that social relationships and collaborative behaviors among people, who are involved in enacting a workflow procedure, affect the overall performance as well as the degrees of working productivity in performing the real business operations under the control of workflow-supported organizations [6]. As a consequence, research and development issues [7-12] of converging the concept of social network and its analysis methods upon workflow-supported people (so-called workflow-performers) have been emerging in the literature.

Our key contribution in this paper is to propose a theoretical framework and its related formalisms for measuring how much close to other workflow-performers by using the social network analysis techniques, particularly the closeness centrality analysis formulas [5]. The centralization of workflow-performers is a typical social network analysis technique identifying the important or prominent performers within a workflow procedure by summarizing the structural relationships among all the performers. The most widely used centralization measures are degree[1], closeness[2], betweenness[3], and eigenvalue. These measures vary in their applicability to non-directed and directed relations, and differ at the individual performer and the group performers of the partial or complete workflow procedure levels. In this paper, we confine the scope of the measurements to the closeness centralization measurement for individual and group workflow-performers within a workflow procedure. The closeness centralization measurement reflects how near a workflow-performer is to the other workflow-performers in enacting a workflow procedure, and through which we can numerically measure and calculate the degree of work-intimacy and collaboration of each workflow performer, which implies how quickly a workflow-performer can interact with others by directly communicating or through very few intermediaries. The eventual goal of the framework is to extensively apply the degree of work-intimacy and collaboration to all performers involved in a workflow model, a workflow package (a group of inter-relevant workflow models), and a group of workflow packages on a workflow-supported organization.

[1] The degree centrality measures the extent to which a workflow-performer connects to all others.
[2] The closeness centrality measures how near a workflow-performer is to the others.
[3] The betweenness centrality measures how other workflow-performers control or mediate the relations between dyads that are not directly connected.

In terms of the composition of the paper, we describe the conceptual backgrounds of this research, in first. In the consecutive section, we expatiate the detailed formalisms of the theoretical framework consisting of discovery phase, analysis phase, visualization phase, in company with an operational example, and finalize the practical implications of the proposed closeness centralization measurements in a workflow-supported organization. Finally, we describe the literature survey result related to the topics of discovering, analyzing, and quantitating the workflow-supported closeness centralization measurements among performers.

2. Conceptual Backgrounds and Contributions

This section starts from shortly introducing the basic concept of information control net (ICN) [2] as a formal methodology for describing workflow models. In the information control net, a workflow model is described by six essential entity types and their associative relationships. Out of the essential entity types, the human-related one is the performer entity type representing a group of workflow-performers assigned to enact the corresponding workflow model. Next, we elucidate the conceptual background and rationale for measuring closeness centralizations among those workflow-performers in an ICN-based workflow model.

2.1 Information Control Net

The information control net [2] defines a workflow model formally and graphically by capturing the essential properties of workflow procedures such as activities and their temporal precedence, invoked applications, roles, performers, and input/output repositories. In this section, we simply introduce the information control net through the formal notations of the workflow's essential entity types. The following **[Definition 1]** is a formal definition of information control net and its functional components returning the various associative relationships of workflow model, such as activity precedence (control flow), activity-role association, activity-relevant data association (data flow), activity-invoked application association, activity-transition condition association, and role-performer association information.

[Definition 1] Information Control Net (ICN) for formally defining workflow model. A basic **ICN** is 8-tuple $\mathbf{\Gamma} = (\delta, \rho, \lambda, \varepsilon, \pi, \kappa, \mathbf{I}, \mathbf{O})$ over a set of **A** activities (including a set of group activities), a set of $\mathbf{E} \subseteq (\mathbf{A} \times \mathbf{A})$ edges (pairs of activities), a set **T** of transition conditions, a set **R** of repositories, a set of **G** of invoked application programs, a set of **P** of roles, and a set of **C** of actors (including a set of actor groups), where $\wp(\ )$ represents a power set:

- **I** is a finite set of initial input repositories, assumed to be loaded with information by some external process before execution of the ICN;
- **O** is a finite set of final output repositories, perhaps containing information used by some external process after execution of the ICN;
- $\delta = \delta_i \cup \delta_o$
  where, δ_o: $\mathbf{A} \rightarrow \wp(\mathbf{A})$ is a multi-valued mapping function from an activity to its sets of (immediate) successors, and δ_i: $\mathbf{A} \rightarrow \wp(\mathbf{A})$ is a multi-valued mapping function from an activity to its sets of (immediate) predecessors;
- $\rho = \rho_i \cup \rho_o$

where ρ_o: $\mathbf{A} \rightarrow \wp(\mathbf{R})$ is a single-valued mapping function from an activity to its set of output repositories, and ρ_i: $\mathbf{A} \rightarrow \wp(\mathbf{R})$ is a single-valued mapping function from an activity to its set of input repositories;

– $\lambda = \lambda_a \cup \lambda_g$

where λ_g: $\mathbf{A} \rightarrow \mathbf{G}$ is a single-valued mapping function from an activity to its invoked application program, and λ_a: $\mathbf{G} \rightarrow \wp(\mathbf{A})$ is a single-valued mapping function from an invoked application program to its set of associated activities;

– $\varepsilon = \varepsilon_a \cup \varepsilon_p$

where ε_p: $\mathbf{A} \rightarrow \wp(\mathbf{P})$ is a single-valued mapping function from an activity to a role, and ε_a: $\mathbf{P} \rightarrow \wp(\mathbf{A})$ is a single-valued mapping function from a role to its set of associated activities;

– $\pi = \pi_p \cup \pi_c$

where π_c: $\mathbf{P} \rightarrow \wp(\mathbf{C})$ is a single-valued mapping function from a role to its set of associated performers, and π_p: $\mathbf{C} \rightarrow \wp(\mathbf{P})$ is a single-valued mapping function from a performer to its set of associated roles;

– $\kappa = \kappa_i \cup \kappa_o$

where κ_i: $\mathbf{E} \rightarrow \wp(\mathbf{T})$ is a single-valued mapping function from an edge to a set of control-transition conditions; and κ_o: $\mathbf{T} \rightarrow \wp(\mathbf{E})$ is a single-valued mapping function from a control-transition condition to a set of edges.

2.2 Key Contributions: Closeness Centralization Measurement and Visualization in a Workflow-Supported Organization

Like the information control net, almost all the workflow models commonly employ the five essential entity types, such as activity, role, performer, repository and application entity-types, to represent organizational works and their procedural collaborations. Through the associative relationships between performer entity type and others, we can obtain human-centered organizational knowledge such as behavioral, social, informational, collaborative, and historical knowledge. Therefore, we can interpret the workflow management systems as "people systems" that must be designed, deployed, and understood within their social and organizational contexts. The people systems ought to be able to support any formations of collaborative activities among people, which eventually build up the human-centered collaborative knowledge as the most influential and meaningful organizational knowledge. The authors' research group has sought the most reasonable metric units for evaluating the degrees of collaborations among people in the workflow-supported people system, and we have found one of them out at last, which is Centrality[4] [5] stemmed from the social network literature. The most widely used centrality measures are degree, closeness, betweenness, and eigenvalue. In this paper, we actively adopt the concept of closeness centrality in quantifying the degree of collaboration among people allotted into a workflow model.

The human-centered collaborative knowledge in a workflow-supported organization can be discovered by exploring the associative relationships between performers and activities from the corresponding workflow models and/or their enactment events histories. As shown in

[4] Centrality, where a prominent actor has high involvement in many relations, regardless of whether sending and receiving ties, in a social network.

Fig. 1, a specific workflow model is defined by a group of activities and their temporal enactment sequences, and it is associated with a group of performers taking charge of enacting its activities. In the information control net, the associations between activities and performers are defined through a group of roles. The activity-performer association is not a direct association but a transitive association, and so it is formed through activity-role associations and role-performer associations. Note that Role is a named designator for one or more participants which conveniently acts as the basis for partitioning of work skills, access controls, execution controls, and authority / responsibility, and Performer is a person that can fulfill roles to execute, to be responsible for, or to be associated with activities of an information control net. The activity-performer associations can be transitively obtained from the activity-role associations and the role-performer associations. We know that the activity-performer association is divided by two directed associations—activity-to-performer association and performer-to-activity association—and both are many-to-many relationships, which imply that not only more than one performers can participate in enacting an activity, but also a performer is able to participate in enacting one or more activities.

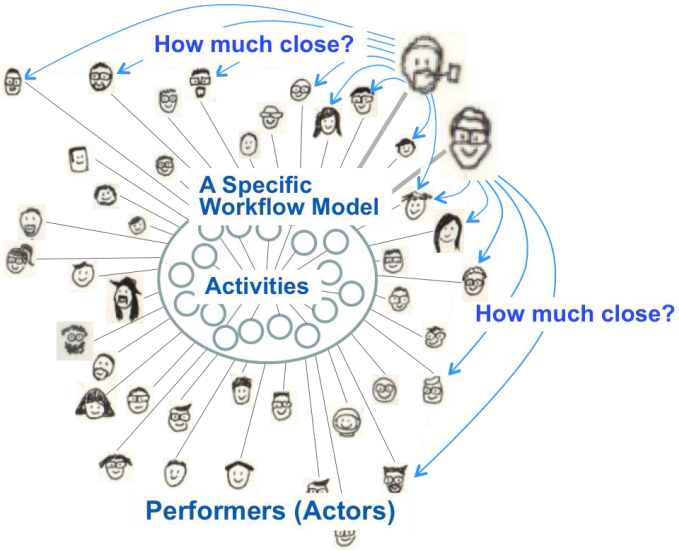

Fig. 1. Performers' Involvement and Closenesses on a Specific Workflow Model

We are particularly interested in adopting the concept of closeness centrality to measure the degree of work-intimacy and collaboration among performers in enacting a corresponding workflow model. The concept was originally developed to reflect how near a node is to the other nodes in a social network, and so the semantic significance of closeness and distance refer to how quickly an actor can interact with others. In the domain of workflow-supported organizational knowledge, the performer's closeness centralization concept can be interpreted as the extent to how much close a specific performer is to the others on a flow of works. **Fig. 1** shows the conceptual significance of the performer's closeness centralization. The activity-performer associations eventually form a flow of works among the workflow-performers, which can be represented by the actor-based workflow model [1] or the workflow-supported social network model [13], both of which were proposed by the authors' research group. Then, on a workflow-supported social network, it might be quite in the nature of things to raise the questions as followings:

- Who is the most important or prominent performer(s) interacting the most tightly with others in enacting a specific workflow procedure?

- How near is the most prominent performer to others in a workflow-supported org-social network?
- What is the average distance (or closeness) among performers in a workflow-supported org-social network? In other words, how quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries?

Conclusively, the answers to the questions ought to be able to convey a very valuable and meaningful insight to the workflow-supported organization. The primary rationale of the closeness centralization concept is on the questions and answers section. A theoretical framework to be expatiated in the next consecutive sections of this paper covers from discovering a shape of workflow-performers' collaborative relationships through a workflow-supported social network to analyzing their closeness centralization measures by mathematically extending some of the well-known closeness centrality formulas [5] in the social network analysis literature. Ultimately, the theoretical framework can be implemented as an organizational intelligent system that is able to quantitatively answer to the questions through the closeness centralization concept and measurement—closeness-centrality—at both individual and group levels of the workflow-supported organization.

3. The Theoretical Framework

In this section, we expatiate on a theoretical framework for measuring the closeness centralizations that enable us to quantify the levels of work-intimacy and collaboration among workflow-performers. The framework is a kind of procedural framework that comprises three stepwise phases with five functional transformations, as illustrated in **Fig. 2**. The phases are discovery, analysis, and visualization phases, and the functional transformations are `ICN-to-WsoN`, `WsoN-to-SocioMatrix`, `SocioMatrix-to-DistanceMatrix`, `DistanceMatrix-to-CCV`, and `CCV-to-ccGraphML` transformations.

- Discovery Phase
  - `ICN-to-WsoN` Transformation: Building a workflow-supported org-social network model from an information control net.
  - `WsoN-to-SocioMatrix` Transformation: Constructing four types of SocioMatrices from a workflow-supported org-social network model.
- Analysis Phase
  - `SocioMatrix-to-DistanceMatrix` Transformation: Creating a DistanceMatrix from a SocioMatrix by applying the geodesic (shortest) distance formulas.
- Quantitation Phase
  - `DistanceMatrix-to-CCV` Transformation: Building up a closeness centrality vector on the DistanceMatrix by applying the closeness centrality formulas.

In the next consecutive subsections, we describe the details of these phases and functional transformations of the theoretical framework through a series of formulas and algorithms, and their operational examples.

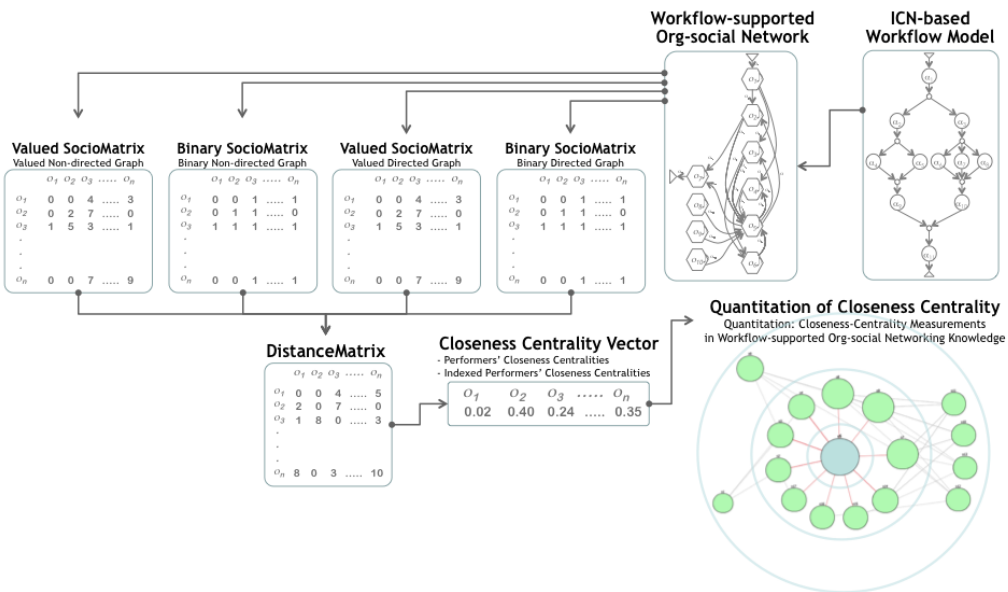

Fig. 2. The Theoretical Framework for Workflow-Performers' Closeness Centralities

3.1 The Discovery Phase

We start from introducing the basic concept and definition of a performer-flow graph that enables us to efficiently calculate the closeness centralization measurements. The performer-flow graph is discovered by analyzing workflow-performers' associative relationships with activities in a workflow procedure. For the sake of the closeness centralization measurements, the performer-flow graph needs to be represented by a theoretical notation as well as a mathematical notation. This graph's formal representation is defined by the workflow-supported org-social network model [9,10,13], which is abbreviated as WsoN, and its mathematical representation is a form of matrix, which is called SocioMatrix [5]. In consequence, the discovery phase of the performer-flow graph from an information control net consists of two of these functional transformations, such as the ICN-to-WsoN Transformation and the WsoN-to-SocioMatrix Transformation.

3.1.1 The ICN-to-WsoN Transformation

The purpose of this transformation is to functionally generate a performer-flow graph from an information control net. The performer-flow graph is formed by the activity-performer associations that can be transitively obtained from the activity-role associations and the role-performer associations in the information control net, as followings:

- The activity-role association: for any activity (α), $\{\alpha \mid \varepsilon_p(\alpha) = \{\eta_i\} \circ \eta_i \in \mathbf{P}\}$, where **P** is the set of roles, $\{\eta_1, \eta_2, ..., \eta_n\}$, means that the activity α is associated with a single role out of **P**; also, for any role(η), $\{\eta \mid \varepsilon_a(\eta) = \{\alpha_s, ..., \alpha_m\} \wedge \{\alpha_s, ..., \alpha_m\} \subset \mathbf{A}\}$, where **A** is the set of activities, $\{\alpha_1, \alpha_2, ..., \alpha_m\}$, means that the role η is associated with one or more activities out of **A**. Summarily, activity-to-role association is one-to-one relationship, whereas role-to-activity association is one-to-many relationship.
- The role-performer association: for any role(η), $\{\eta \mid \pi_c(\eta) = \{\varnothing_s, ..., \varnothing_k\} \wedge \{\varnothing_s, ..., \varnothing_k\} \subset \mathbf{C}\}$,

where **C** is the set of performers, $\{ø_1, ø_2, ..., ø_n\}$, means that the role η is associated with one or more performers out of **C**; also, for any performer(ø), $\{ø \mid \pi_p(ø) = \{\eta_s, ..., \eta_m\} \wedge \{\eta_s, ..., \eta_m\} \subset \mathbf{P}\}$, where **P** is the set of roles, means that the performer ø is associated with one or more roles out of **P**. Summarily, both role-to-performer association and performer-to-role association are many-to-many relationships.

- Based upon these two types of associations, we are able to transitively obtain the activity-to-performer associations from an information control net, and we know that both the activity-to-performer association and performer-to-activity association are many-to-many relationships. Conclusively speaking, not only more than one performers can participate in enacting an activity, but also a performer is able to participate in enacting one or more activities.

[Definition 2] Workflow-Supported Organizational Social (Org-Social) Network Model. The workflow-supported org-social network model is formally defined as $\mathbf{\Lambda} = (\sigma, \psi, S, E)$, over a set **C** of performers, and a set **A** of activities, where

- S is a finite set of coordinators or coordinator-groups connected from some external workflow-supported org-social network models;
- E is a finite set of coordinators or coordinator-groups connected to some external workflow-supported org-social network models;
- $\sigma = \sigma_i \cup \sigma_o$ /* Control-Precedence Relationships */

  where, σ_o: $\mathbf{C} \rightarrow \wp(\mathbf{C})$ is a multi-valued function mapping a performer to its sets of (immediate) candidate-successors, and σ_i: $\mathbf{C} \rightarrow \wp(\mathbf{C})$ is a multi-valued function mapping a performer to its sets of (immediate) candidate-predecessors;
- $\psi = \psi_i \cup \psi_o$ /* Activity-Acquisition Relationships */

  where, ψ_i: $\mathbf{C} \rightarrow \wp(\mathbf{C})$ is a multi-valued function returning a bag[5] of previously worked activities, ($\mathbf{K} \subseteq \mathbf{A}$), on directed arcs, $(\sigma_i(ø), ø)$, $ø \in \mathbf{C}$, from $\sigma_i(ø)$ to ø; and ψ_o: $\mathbf{C} \rightarrow \wp(\mathbf{C})$ is a multi-valued function returning a set of acquisition activities, ($\mathbf{K} \subseteq \mathbf{A}$), on directed arcs, $(ø, \sigma_o(ø))$, $ø \in \mathbf{C}$ from ø to $\sigma_o(ø)$;

The performer-flow graph is formally and graphically represented by the workflow-supported org-social network model, as given in the formal definition, **[Definition 2]**. The behaviors of the model are revealed through incoming and outgoing directed arcs labeled as activities between a pair of associated performers. The directed arcs manifest two kinds of behaviors—control-precedence and activity-acquisition—between the associated performers, through which we are able to obtain the work-precedence (candidate-predecessor knowledge/candidate-successor knowledge) knowledge and the activity-acquisition knowledge among performers in a workflow procedure. In terms of defining the performer's predecessors and successors, we would use the prepositional word, "candidate," because a role-performer association is a one-to-many mapping relationship and the performer selecting and binding mechanism has to choose one out of the assigned performers of the role during a corresponding workflow instance's execution time.

In principle, the workflow-supported org-social network model is graphically represented by a directed graph characterized by some combinations of multiple-incoming arcs,

[5] The bag theory is same to the set theory except allowing duplicated members.

multiple-outgoing arcs, cyclic, self-transitive, and multiple-activity associations on arcs, and which needs to be transformed to an undirected graph. For measuring the closeness centralities among the associated performers, the performer-flow graph, which is a directed graph, needs to be transformed into an undirected graph, too.

ICN-to-WsoN Transformation Algorithm:
Input An Information Control Net, $\mathbf{\Gamma} = (\delta, \rho, \lambda, \varepsilon, \pi, \kappa, \mathbf{I}, \mathbf{O})$;
Output A Workflow-Supported Org-Social Network Model, $\mathbf{\Lambda} = (\sigma, \psi, \mathbf{S}, \mathbf{E})$;
Begin Procedure
  For ($\forall \alpha \in \mathbf{A}$) **Do**
    Begin
      /* $\sigma = \sigma_i \cup \sigma_o$ */
      Add all members of $\pi_c(\varepsilon_p(\alpha))$ **To** σ_i(each member of $\pi_c(\varepsilon_p(\delta_o(\alpha))))$;
      Add all members of $\pi_c(\varepsilon_p(\delta_o(\alpha)))$ **To** σ_o(each member of $\pi_c(\varepsilon_p(\alpha)))$;
      /* $\psi = \psi_i \cup \psi_o$ */
      Add all pairs of $(\alpha, ø)$, $\forall ø \in \pi_c(\varepsilon(\alpha))$ **To** ψ_i(each of $\pi_c(\varepsilon_p(\delta_o(\alpha))))$;
      Add all pairs of $(\alpha, ø)$, $\forall ø \in \pi_c(\varepsilon_p(\delta_o(\alpha)))$ **To** ψ_o(each of $\pi_c(\varepsilon_p(\alpha)))$;
    End
End Procedure

The above algorithm shows the ICN-to-WsoN transformation procedure. Again, it is important to emphasize that the workflow-supported org-social network model is not modeled or designed but automatically transformed from an information control net. So, the authors' research group devised the formal transformation methodology [1,2,9] that algorithmically analyzes the human-centered associations of an information control net. As described at the above algorithm, it needs, as input, sets of the human-centered associations—ε_p (activity-role associations) and π_c (role-performer associations)—based on δ_o(control-flow collaborations). As output, it generates the necessary sets—$\sigma = \sigma_i \cup \sigma_o$ (performer-precedence perspective) and $\psi = \psi_i \cup \psi_o$ (activity-acquisition perspective)—of the workflow-supported org-social network model by transitively applying the activity-role associations and the role-performer associations. Through these generated sets, we are able to build a performer-flow graph for the closeness centralization measurements.

As an operational example, we apply the algorithm to the hiring information control net introduced in [2]. The transformed result of the performer-flow model is graphically represented in the right-hand side of **Fig. 3**. Due to the page limitation, we won't provide the details of the formal representations of the input model and the output model. In terms of the performer's closeness centralization measurements, we know that there are seventeen performers on the performer-flow graph, and the geodesic (shortest) distances between the performer node, $ø_1$ and others, $ø_2$, $ø_3$, $ø_4$, $ø_5$, $ø_6$, $ø_7$, $ø_8$, $ø_9$, $ø_{10}$, $ø_{11}$, $ø_{12}$, $ø_{13}$, $ø_{14}$, $ø_{15}$, $ø_{16}$, $ø_{17}$, are 1, 1, 1, 2, 2, 3, 3, 3, 4, 4, 4, 4, 5, 5, 5, and 2, respectively. These geodesic distances come out of the directed performer-flow graph. However, we also know that they ought to be recalculated on the undirected performer-flow graph.

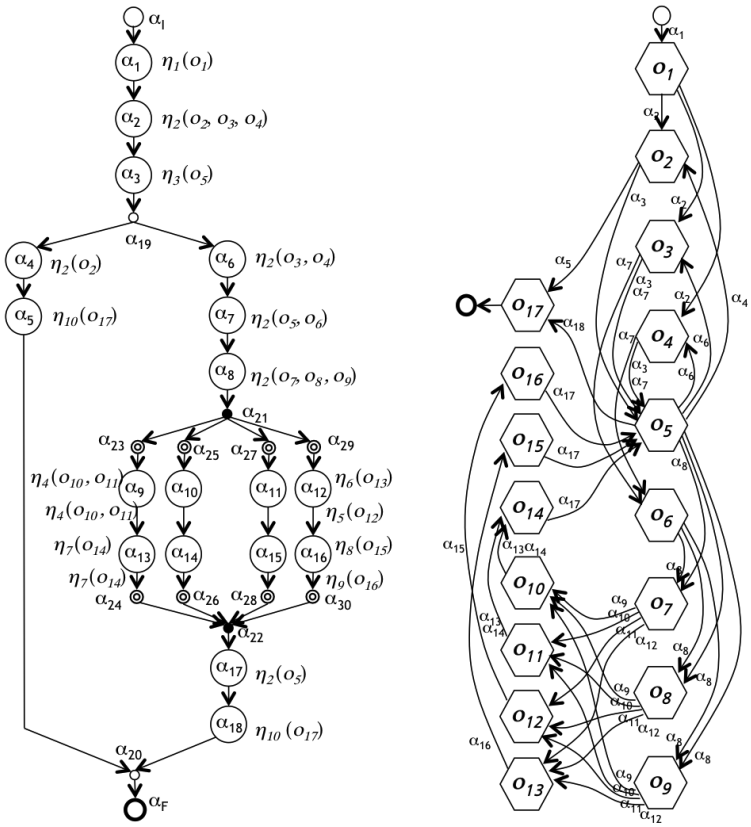

Fig. 3. The Hiring Information Control Net [15] and Its Performer-Flow Graph (WsoN)

Binary Directed SocioMatrix Transformation Algorithm:
Input A workflow-supported org-social network, $\mathbf{\Lambda} = (\sigma, \psi, \mathbf{S}, \mathbf{E})$;
Output Two symmetric binary SocioMatrices, $\mathbf{Z}^{b}_{in}[N, N]$ and $\mathbf{Z}^{b}_{out}[N, N]$,
where N is the number elements in the set of **C** actors.

Begin Procedure
Initialize all entries of $\mathbf{Z}^{b}_{in}[N, N]$ To Zeroes;
Initialize all entries of $\mathbf{Z}^{b}_{out}[N, N]$ To Zeroes;
For ($\forall \text{ø} \in \mathbf{C}$) Do
Begin
/* The Incoming Relations of $\mathbf{Z}^{b}_{in}[N, N]$ */
Set One **To** entries of $\mathbf{Z}^{b}_{in}[\text{ø}$, each member of $\sigma_i(\text{ø})]$;
/* The Outgoing Relations of $\mathbf{Z}^{b}_{out}[N, N]$ */
Set One **To** entries of $\mathbf{Z}^{b}_{out}[\text{ø}$, each member of $\sigma_o(\text{ø})]$;
End
End Procedure

3.1.2 The WsoN-to-SocioMatrix Transformation

The performer-flow graph is formally represented by the workflow-supported org-social network model, and its mathematical representation is expressed in terms of SocioMatrix [5]

introduced in the social network literature. In order to mathematically measure the closeness centralizations, the performer-flow graph needs to be transformed in SocioMatrix by a WsoN-to-SocioMatrix transformation algorithm. SocioMatrix can be refined on two groups of subtle matrices—binary directed/undirected SocioMatrix and valued directed/undirected SocioMatrix. We use to construct a sociogram [5] that is a two-dimensional diagram for depicting the precedence relationships among performers. The term, directed, indicates the directed-precedence relationships or ties from one at the tail to another at the arrowhead, whereas the term, undirected (no arrowheads), implies mutual-precedence relationships. Likewise, when a directed/undirected performer-flow graph is transformed to SocioMatrix, the term, binary, implies the most basic measurement, presence or absence of a tie, which is a dichotomy indicated by the binary value of 1 or 0, respectively; also SocioMatrix may include valued cells, reflecting the intensity of relationships or ties, such as frequency of performer-flows, tie strength, or magnitude of associations, and therefore the cell entries in SocioMatrix can vary from 0 to the maximum level of dyadic interactions.

The authors' research group had devised a series of algorithms that are able to transform a workflow-supported org-social network into four types of SocioMatrix. Without any further explanation, we simply introduce these `WsoN-to-SocioMatrix` transformation algorithms as followings, each of which produces binary/directed SocioMatrix ($\mathbf{Z}^b_{in}$[N, N], $\mathbf{Z}^b_{out}$[N, N]), binary/undirected SocioMatrix ($\mathbf{Z}^b$[N,N]), valued/directed SocioMatrix ($\mathbf{Z}^v_{in}$[N,N], $\mathbf{Z}^v_{out}$[N,N]), and valued/undirected SocioMatrix ($\mathbf{Z}^v$[N,N]), where N is the number of performers in a workflow-supported org-social network.

Binary unDirected SocioMatrix Transformation Algorithm:
Input A workflow-supported org-social network, $\mathbf{\Lambda} = (\sigma, \psi, \mathbf{S}, \mathbf{E})$;
Output A symmetric binary SocioMatrix, $\mathbf{Z}^b$[N, N],
where N is the number elements in the set of **C** actors(Performers).
Begin Procedure
Initialize all entries of $\mathbf{Z}^b$[N, N] To Zeroes ;
For ($\forall ø \in \mathbf{C}$) **Do**
Begin
/* Set the Incoming Relations to $\mathbf{Z}^b$[N, N] */
Set One **To** entries of $\mathbf{Z}^b$[ø, each member of σ_i(ø)];
/* Set the Outgoing Relations to $\mathbf{Z}^b$[N, N] */
Set One **To** entries of $\mathbf{Z}^b$[ø, each member of σ_o(ø)];
End
End Procedure

In order to verify the devised WsoN-to-SocioMatrix transformation algorithms, we directly apply the binary/undirected SocioMatrix transformation algorithm to the formal representation of the workflow-supported org-social network transformed from the hiring information control net of **Fig. 3**. **Table 1** shows the binary/undirected SocioMatrix, $\mathbf{Z}^b$[N,N], successfully transformed by the algorithm. Note that it is possible to generate a valued/undirected SocioMatrix by adding two of the symmetric valued SocioMatrices, $\mathbf{Z}^v_{in}$[N,N] and $\mathbf{Z}^v_{out}$[N,N]; in this case, then the values of the entries might be indicating the frequencies of performer-precedence relationships (or activity-acquisition relationships) between the paired performers.

Valued Directed SocioMatrix Transformation Algorithm:
Input A workflow-supported org-social network, $\mathbf{\Lambda} = (\sigma, \psi, \mathbf{S}, \mathbf{E})$;
Output Two symmetric valued SocioMatrices, $\mathbf{Z}^{v}_{in}[N, N]$ and $\mathbf{Z}^{v}_{out}[N, N]$,
where N is the number elements in the set of **C** actors (Performers).
Begin Procedure
Initialize all entries of $\mathbf{Z}^{v}_{in}[N, N]$ To Zeroes;
Initialize all entries of $\mathbf{Z}^{v}_{out}[N, N]$ To Zeroes;
For ($\forall$ ø $\in$ **C**) **Do**
Begin
/* Add the Incoming Relations to Zvin[N, N] */
Add One **To** entries of $\mathbf{Z}^{v}_{in}[ø$, each member of $\sigma_i(ø)]$;
/* Add the Outgoing Relations to Zvout[N, N] */
Add One **To** entries of $\mathbf{Z}^{v}_{out}[ø$, each member of $\sigma_o(ø)]$;
End
End Procedure

Valued unDirected SocioMatrix Transformation Algorithm:
Input A workflow-supported org-social network, $\mathbf{\Lambda} = (\sigma, \psi, \mathbf{S}, \mathbf{E})$;
Output A symmetric valued SocioMatrix, $\mathbf{Z}^{v}[N, N]$,
where N is the number elements in the set of **C** actors (Performers).
Begin Procedure
Initialize all entries of $\mathbf{Z}^{v}[N, N]$ To Zeroes;
For ($\forall$ ø $\in$ **C**) **Do**
Begin
/* Add the Incoming Relations to $\mathbf{Z}^{v}[N, N]$ */
Add One **To** entries of $\mathbf{Z}^{v}[ø$, each member of $\sigma_i(ø)]$;
/* Add the Outgoing Relations to $\mathbf{Z}^{v}[N, N]$ */
Add One **To** entries of $\mathbf{Z}^{v}[ø$, each member of $\sigma_o(ø)]$;
End
End Procedure

3.2 The Analysis Phase

As stated in the conceptual background section, we are interested in quantitatively measuring the degree of closeness centralization by borrowing the well-known formulas [5] in the social network analysis literature. The analysis phase carries out the functional transformation, the SocioMatrix-to-DistanceMatrix transformation to calculate the geodesic distances among performers.

3.2.1 The SocioMatrix-to-DistanceMatrix Transformation

Based upon the SocioMatrices, $\mathbf{Z}^{b}_{in}[N,N]$, $\mathbf{Z}^{b}_{out}[N,N]$, $\mathbf{Z}^{b}[N,N]$, $\mathbf{Z}^{v}_{in}[N,N]$, $\mathbf{Z}^{v}_{out}[N,N]$, and $\mathbf{Z}^{v}[N,N]$, we are able to calculate the closeness centrality measures by applying the formula given in (1) [5].

- The Index of Individual Closeness Centrality

$$Cc(\phi_i) = \frac{1}{\sum_{j=1}^{N} d(\phi_i, \phi_j)} (i \neq j) \tag{1}$$

Formula (1) is for measuring an individual performer's closeness centrality. The term, $d(ø_i, ø_j)$, in the denominator is a function of geodesic distance that is the length of the shortest path out of all reachable paths from $ø_i$ to $ø_j$. The conceptual implication of the individual closeness centrality refers to how quickly a performer can interact with others by communicating directly or through very few intermediaries. Conclusively, from one of the SocioMatrices with N performers, the index of individual closeness centrality is computed as the inverse of the sum of the geodesic distances between performer $ø_i$ and the (N − 1) other performers. The SocioMatrix-to-DistanceMatrix transformation is charged with the function of geodesic distances, $d(ø_i, ø_j)$, for all workflow-performers by iteratively applying the function for N times as many workflow-performers.

The following algorithm is the pseudo-coded function carrying out the SocioMatrix-to-DistanceMatrix transformation through the procedure name of *geoDistanceMeasurement*( ) with a recursive subroutine, *geoDistance*( ), which returns a geodesic distance of the performer dyad input. We assume that SocioMatrix as input of the algorithm is a Binary/unDirected SocioMatrix, $\mathbf{Z}^b$[N, N].

```
SocioMatrix-to-DistanceMatrix Transformation Algorithm:
Global A Set of Individual Performers, C;
Global A Set of Traversed Individuals, T;
Global A Set of Direct-tied Individuals, D;
Global A Set of Distance Values, depth[N];

Procedure Name: geoDistanceMeasurement( )
Input A Binary/unDirected SocioMatrix, Z^b[N, N];
Output A Geodesic (Shortest) Distance Matrix, DistanceMatrix[N, N];
Begin Procedure
    For ( ∀ø_i ∈ C )
        For ( ∀ø_j ∈ C, ø_i ≠ ø_j )
            Switch ( Z[ø_i, ø_j] )
                Case 1: /* direct tie between ø_i and ø_j. */
                    DistanceMatrix[ø_i, ø_j ] ← 1;
                    break;
                Case 0: /* no direct tie between ø_i and ø_j. */
                    Initialize (depth(ø_1) . . . depth(ø_n)) ← 1;
                    T ← ø_i;
                    DistanceMatrix[ø_i, ø_j ] ← geoDistance(ø_i,ø_j);
                    break;
        Rof
    Rof
    Return DistanceMatrix[N, N];
End Procedure
```

Procedure Name: *geoDistance*( )
Input The source individual, $ø_s$, and the destination individual, $ø_d$;
Output The shortest distance between $ø_s$ and $ø_d$;
Begin Procedure
  D ← ∅;
  T ← **T** ∪{$ø_s$};
  For (∀$ø_i$ ∈ **C**)
    If (**Z**[$ø_s$, $ø_i$] == 1) **D** ← **D** ∪ {$ø_i$}; **Fi**;
  Rof;
  For (∀øi ∈ D)
    If (**Z**[$ø_i$, $ø_d$] == 1)
      depth($ø_i$) ← *depth*($ø_i$) + 1;
      Return *depth*($ø_i$);
    Fi;
  Rof;
  For (∀$ø_i$ ∈D ∧ $ø_i$ ∉ **T**)
    depth($ø_i$) ← *geoDistance*($ø_i$, $ø_d$) + 1;
    D ← **D** − {$ø_i$};
  Rof;
  Return ***minimum***{*depth*($ø_1$), ..., *depth*($ø_m$)}; /* *m* is the # of members in **D**. */
End Procedure

As you see, the time complexity of the algorithm is $O(N^2)$. The main procedure named *geoDistanceMeasurement*( ) forms a typical double-loop construct with a recursive function, *geoDistance*( ), that can be computed in a constant time, O(1), because the number of performers in the set, **D**, ought to be much smaller than the number of individual performers. By using the above algorithm devised in this paper, we are able to eventually measure not only the standardized index of individual closeness centrality, but also the index of group closeness centrality for a workflow-supported org-social network.

As an operational example, we apply the SocioMatrix-to-DistanceMatrix transformation algorithm to the binary/undirected SocioMatrix, $\mathbf{Z}^b$[N, N], of **Table 1**. The calculated geodesic distance matrix, *DistanceMatrix*[N, N], is the following **Table 2**. Remind that from the directed performer-flow graph we calculated, as an example, the geodesic (shortest) distances between the performer node, $ø_1$ and others, $ø_2$, $ø_3$, $ø_4$, $ø_5$, $ø_6$, $ø_7$, $ø_8$, $ø_9$, $ø_{10}$, $ø_{11}$, $ø_{12}$, $ø_{13}$, $ø_{14}$, $ø_{15}$, $ø_{16}$, $ø_{17}$, were 1, 1, 1, 2, 2, 3, 3, 3, 4, 4, 4, 4, 5, 5, 5, and 2, respectively. In the table of the binary/undirected SocioMatrix, we recognize the different result for the same case ($ø_1$), like 1, 1, 1, 2, 2, 3, 3, 3, 4, 4, 4, 4, 3, 3, 3, and 2, in the first row of the table.

Table 1. Binary/unDirected SocioMatrix ($\mathbf{Z}^b$[N, N]) of **Fig. 3**

C	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$	$\emptyset_8$	$\emptyset_9$	$\emptyset_{10}$	$\emptyset_{11}$	$\emptyset_{12}$	$\emptyset_{13}$	$\emptyset_{14}$	$\emptyset_{15}$	$\emptyset_{16}$	$\emptyset_{17}$
$\emptyset_1$	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
$\emptyset_2$	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
$\emptyset_3$	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
$\emptyset_4$	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
$\emptyset_5$	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	1
$\emptyset_6$	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0
$\emptyset_7$	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0
$\emptyset_8$	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0
$\emptyset_9$	0	0	0	0	1	1	0	0	0	1	1	1	1	0	0	0	0
$\emptyset_{10}$	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0
$\emptyset_{11}$	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0
$\emptyset_{12}$	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0
$\emptyset_{13}$	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0
$\emptyset_{14}$	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0
$\emptyset_{15}$	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
$\emptyset_{16}$	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
$\emptyset_{17}$	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0

Table 2. Geodesic Distance Matrix (*DistanceMatrix*[N, N]) from **Table 1**

C	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	$\emptyset_4$	$\emptyset_5$	$\emptyset_6$	$\emptyset_7$	$\emptyset_8$	$\emptyset_9$	$\emptyset_{10}$	$\emptyset_{11}$	$\emptyset_{12}$	$\emptyset_{13}$	$\emptyset_{14}$	$\emptyset_{15}$	$\emptyset_{16}$	$\emptyset_{17}$
$\emptyset_1$	0	1	1	1	2	2	3	3	3	4	4	4	4	3	3	3	2
$\emptyset_2$	1	0	2	2	1	2	2	2	2	3	3	3	3	2	2	2	1
$\emptyset_3$	1	2	0	2	1	1	2	2	2	3	3	3	3	2	2	2	2
$\emptyset_4$	1	2	2	0	1	1	2	2	2	3	3	3	3	2	2	2	2
$\emptyset_5$	2	1	1	1	0	2	1	1	1	2	2	2	2	1	1	1	1
$\emptyset_6$	2	2	1	1	2	0	1	1	1	2	2	2	2	3	3	3	3
$\emptyset_7$	3	2	2	2	1	1	0	2	2	1	1	1	1	2	2	2	2
$\emptyset_8$	3	2	2	2	1	1	2	0	2	1	1	1	1	2	2	2	2
$\emptyset_9$	3	2	2	2	1	1	2	2	0	1	1	1	1	2	2	2	2
$\emptyset_{10}$	4	3	3	3	2	2	1	1	1	0	2	2	2	1	3	3	3
$\emptyset_{11}$	4	3	3	3	2	2	1	1	1	2	0	2	2	1	3	3	3
$\emptyset_{12}$	4	3	3	3	2	2	1	1	1	2	2	0	2	3	3	1	3
$\emptyset_{13}$	4	3	3	3	2	2	1	1	1	2	2	2	0	3	1	3	3
$\emptyset_{14}$	3	2	2	2	1	3	2	2	2	1	1	3	3	0	2	2	2
$\emptyset_{15}$	3	2	2	2	1	3	2	2	2	3	3	3	1	2	0	2	2
$\emptyset_{16}$	3	2	2	2	1	3	2	2	2	3	3	1	3	2	2	0	2
$\emptyset_{17}$	2	1	2	2	1	3	2	2	2	3	3	3	3	2	2	2	0

3.3 The Quantitation Phase

The quantitation phase carries out the functional transformation of the Distance-to-CCV transformation to measure the individual closeness centralizations by using the result (the geodesic distances) of the former transformation. The ultimate goal of the quantitation phase aims to answer to the following essential question:

- How quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries?

That is, through the closeness centrality concept and its measurements we can obtain a reasonable level of quantitation results, which is enough to answer to the above question as

well as the other questions stated in the beginning of the paper. The closeness centrality measures can be applied to the individual performer (individual closeness centrality) as well as the group of performers (group closeness centrality).

3.3.1 The DistanceMatrix-to-CCV Transformation

Based on the geodesic distance matrix, *DistanceMatrix*[N, N], transformed from the SocioMatrix-to-DistanceMatrix transformation function, we eventually measure the closeness centralizations of all the individuals. The following formula (2) is for carrying out the DistanceMatrix-to-CCV transformation. The result of the transformation is the closeness centrality vector, [Cc($ø_1$), ..., Cc($ø_n$)]. Each quantity of the vector is computed as the inverse of the sum of the geodesic distances between its corresponding performer, $ø_i$, and the (N − 1) other performers. As you see, the measured indices computed from formula (2) can never be 0.0, because division by zero is mathematically undefined. Thus, the index of individual closeness centrality cannot be computed for an isolated performer, which is the case of that only a single performer is assigned to enacting all activities of the corresponding workflow procedure. Also, we can predict that the lowest index, which is the case of the highest sum of the geodesic distances between a focal performer and others, comes out from a performer either in a relatively large network or in a small network with relatively long geodesic distances from others.

- The Closeness Centrality Vector

$$[Cc(\phi_i)]_{i=1}^{N} = \left[\frac{1}{\sum_{j=1}^{N} DistanceMatrix[\phi_i, \phi_j]}(i \neq j)\right]_{i=1}^{N} \tag{2}$$

- The Standardized Closeness Centrality Vector

$$\left[C_C^S(\phi_i)\right]_{i=1}^{N} = [(N-1) \cdot Cc(\phi_i)]_{i=1}^{N} \tag{3}$$

Formula (3) is for standardizing the index of individual closeness centrality by multiplying by $(N - 1)$, in which the corresponding performer is excluded from the total number of performers. Suppose that an individual performer has the closest distance to all others, which means that the performer has a direct tie to everyone in the network. Then, the computed values of indexes will be various according to their network sizes. In order to control the size of the network, it is necessary for the individual index to be standardized between 0.0 (even then it is never happened) and 1.0. It allows, so, meaningful comparisons of performers' closeness centralities across different sizes of workflow-supported org-social networks.

DistanceMatrix-to-CCV Transformation Algorithm:
Procedure Name: *ClosenessCenralityMeasurement*( )
Input A Geodesic Distance Matrix, *DistanceMatrix*[N, N];
Output An Individual Closeness Centrality Vector, [$C_C(ø_1)$, ..., $C_C(ø_n)$];
Output A Standardized Closeness Centrality Vector, [$C_C^S(ø_1)$, ..., $C_C^S(ø_n)$];
Initialize
N ← |**C**|; /* Set of Individual Performers, **C** */
Begin Procedure
For ($\forall ø_i \in$ **C**)

For ($\forall ø_j \in \mathbf{C}$, $ø_i \neq ø_j$)

$C_C(ø_i) \leftarrow C_C(ø_i) + DistanceMatrix[ø_i, ø_j]$;

Rof;

$C_C(ø_i) \leftarrow \frac{1}{Cc(ø_i)}$;

$C_C^S(ø_i) \leftarrow C_C(ø_i) \times (N-1)$;

Rof

Return $[C_C(ø_1), ..., C_C(ø_n)]$ and $[C_C^S(ø_1), ..., C_C^S(ø_n)]$;

End Procedure

The following algorithm is a pseudo-coded functional procedure, named as *ClosenessCenralityMeasurement*( ), for implementing the formulas (2) and (3). As you see, the algorithm is a straightforward control-logic transforming a geodesic distance matrix (*DistanceMatrix*[N, N]) to an individual closeness centrality vector, ($[C_C(ø_1), ..., C_C(ø_n)]$), by taking the inverse after summing every column of each row in the matrix, and a standardized individual closeness centrality vector, $[C_C^S(ø_1), ..., C_C^S(ø_n)]$, by multiplying each quantity of the individual closeness centrality vector by (N – 1), as well. Likewise, as an operational example, we apply the algorithm to the geodesic distance matrix of **Table 2**, and the result of the DistanceMatrix-to-CCV Transformation is on **Table 3**. Note that the performer, $ø_5$, has the highest closeness centralization measures in CCV and sCCV as 1/22 and 0.73, respectively. From this truth, we can answer the question, "Who is the most important or prominent performer(s) interacting the most tightly with others in enacting the hiring workflow procedure?". So, the answer is the performer, $ø_5$.

Table 3. Individual Closeness Centrality Vector ($[\boldsymbol{C_C(ø_1), ..., C_C(ø_n)}]$) from **Table 2**

C	$ø_1$	$ø_2$	$ø_3$	$ø_4$	$ø_5$	$ø_6$	$ø_7$	$ø_8$	$ø_9$	$ø_{10}$	$ø_{11}$	$ø_{12}$	$ø_{13}$	$ø_{14}$	$ø_{15}$	$ø_{16}$	$ø_{17}$
CCV	$\frac{1}{43}$	$\frac{1}{33}$	$\frac{1}{33}$	$\frac{1}{33}$	$\frac{1}{22}$	$\frac{1}{31}$	$\frac{1}{27}$	$\frac{1}{27}$	$\frac{1}{27}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{36}$	$\frac{1}{33}$	$\frac{1}{35}$	$\frac{1}{35}$	$\frac{1}{35}$
$sCCV$	.37	.48	.48	.48	.73	.52	.59	.59	.59	.44	.44	.44	.44	.48	.46	.46	.46

3.3.2 Group Closeness Centrality

As the last step of the analysis phase, we remain one more additional transformation to quantify the network-wide degree of closeness centralization, which we would call the sCCV-to-GCC transformation. The network-wide degree of closeness centralization measurement is to quantify the degree of dispersion indicating the hierarchy of closeness centralities within a workflow-supported org-social network. In other words, this measure implies the extent to which performers in a given network differ in their closeness centralities, and it can be calculated by the formula [5] of the index of group closeness centrality as followings:

- The Index of Group Closeness Centrality

$$GCc = \frac{\sum_{i=1}^{N}[C_C^S(\phi^*) - C_C^S(ø_i)]}{\frac{(N-2)(N-1)}{(2N-3)}} \tag{4}$$

Table 4. Group Closeness Centrality (GC_C) from **Table 3**

The Highest Performer, $C_C(\phi^*)$, $C_C^S(\phi^*)$	The Index of GCC, GC_C, The Hiring Workflow Model
ϕ_5, $\frac{1}{22}$, 0.73	0.512

In formula (4), $C_C^S(\phi^*)$ denotes the highest standardized individual closeness centrality measure observed in a given network, and $C_C^S(\phi_i)$ is the standardized individual closeness centrality measure of each of the $(N-1)$ other performers. The maximum value of the index of group closeness centrality ought to be 1.0 when the corresponding network forms completely an uneven dispersion in the standardized individual closeness centrality measures, which is in the case of that a single performer has the maximum measure and all others have the minimum. In contrast, the index of group closeness centrality equals to 0.0 in the case of that every performer has the same individual closeness centrality measure. Conclusively, the index of group closeness centrality in a workflow-supported org-social network ought to be between 0.0 and 1.0. The closer that the index value is to 1.0, the more uneven or hierarchical is the closeness centralizations of performers in a given network; while on the other hand, the closer the index value is to 0.0, then the more the closeness centralization of the network is evenly dispersed. We won't provide the algorithm of the sCCV-to-GCC transformation because of its simple and straightforward logic.

As an operational example, we apply the formula to the standardized individual closeness centrality vector of **Table 3**, and the result is on **Table 4**. Also, **Table 5** shows the geodesic distances from the performer, ϕ_5, who is the most prominent performer in enacting the hiring workflow procedure, to the other performers, and their closeness centrality measures. The direct-tied (its geodesic distance is 1.) nodes with ϕ_5 are ϕ_2, ϕ_3, ϕ_4, ϕ_5, ϕ_7, ϕ_8, ϕ_9, ϕ_{14}, ϕ_{15}, ϕ_{16}, and ϕ_{17}, and the nodes away from ϕ_5 as much as 2-tie (its geodesic distance is 2.) are ϕ_1, ϕ_6, ϕ_{10}, ϕ_{11}, ϕ_{12}, and ϕ_{13}.

Table 5. Geodesic Distances and Closeness Centrality Measures on the Performer, ϕ_5

C	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	ϕ_7	ϕ_8	ϕ_9	ϕ_{10}	ϕ_{11}	ϕ_{12}	ϕ_{13}	ϕ_{14}	ϕ_{15}	ϕ_{16}	ϕ_{17}
ϕ_5	2	1	1	1	**0**	2	1	1	1	2	2	2	2	1	1	1	1
sCCV	.37	.48	.48	.48	**.73**	.52	.59	.59	.59	.44	.44	.44	.44	.48	.46	.46	.46

3.3.3 Visualization of the Quantitation Results

As stated in the introductory statements of the framework, we are particularly interested in visualizing the degree of work-intimacy and collaboration (closeness centrality) of every workflow performer associated with a specific workflow-supported org-social network. At this moment, we would emphasize that, as a future work of the paper, we have a plan to extensively apply the theoretical framework to not only a group of workflow models but also all the organization-wide workflow packages, and then definitely the visualization phase will be the most crucial functionality in the framework and its implemented system.

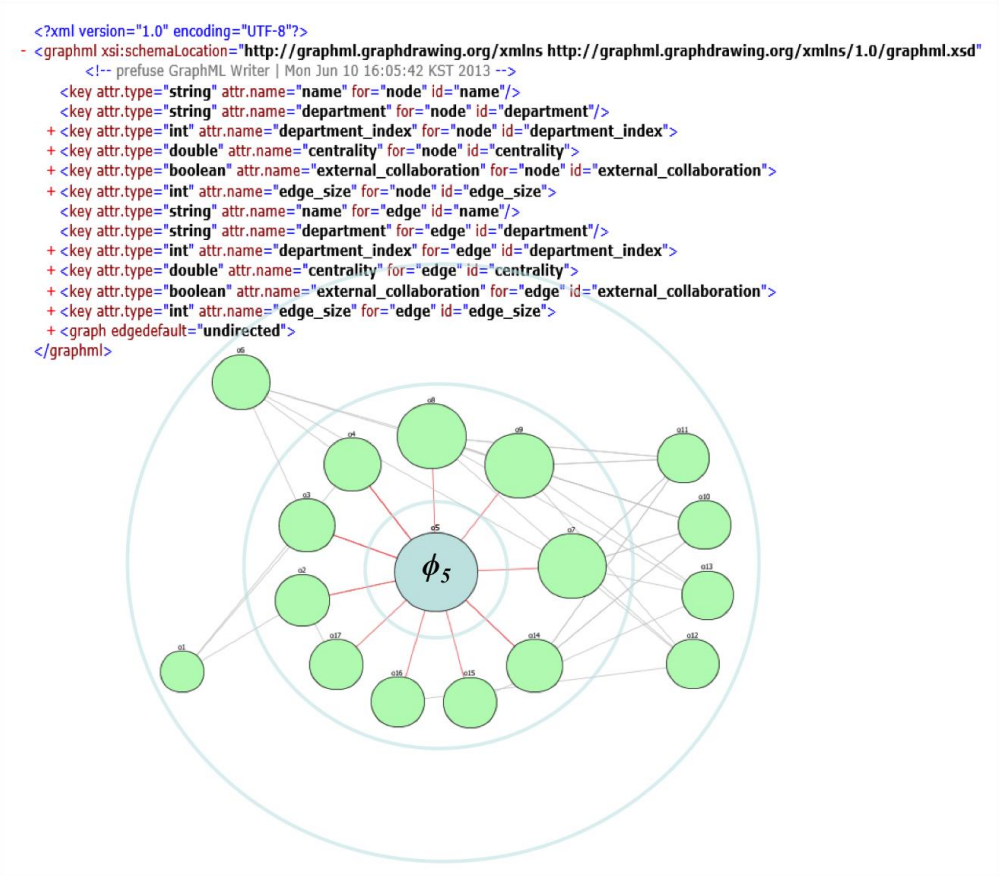

Fig. 4. Closeness Centrality Visualization for the Performer, $ø_5$

As an operational example, **Fig. 5** shows a possible visualization with a screen-snapshot[6] of the visual representation of the individual closeness centrality measures centered from the performer, $ø_5$, who has the highest closeness centrality measure quantitated from the hiring workflow procedure [2]. For the sake of the verification of the visual correctness, we provide the geodesic distances from $ø_5$ to the others and the individual closeness centrality measures in **Table 5**. As you can easily recognize on the colored screen-snapshot of the closeness centralization graph, the centered node ($ø_5$) is the biggest sized circle, the direct-tied (its geodesic distance is 1.) nodes with $ø_5$ are $ø_2$, $ø_3$, $ø_4$, $ø_5$, $ø_7$, $ø_8$, $ø_9$, $ø_{14}$, $ø_{15}$, $ø_{16}$, and $ø_{17}$, and the nodes away from $ø_5$ as much as 2-tie (its geodesic distance is 2.) are $ø_1$, $ø_6$, $ø_{10}$, $ø_{11}$, $ø_{12}$, and $ø_{13}$. Also, it is visually noticeable that the sizes of nodes are figured differently according to the magnitude of the individual closeness centrality index.

4. Related Works

Recently, workflow literature has just begun to focus on social and collaborative structures on process-oriented organizations. The relationship between knowledge management and organizational performance has been the subject of discussion in management literature, and some results [15-17] found out that there is a significant link between human-centered structural knowledge and organizational culture and performance. Our work of the theoretical

[6] This screen-snapshot is captured from the system's closeness centralization measurement module.

framework is one of the pioneering activities for digging up new methodologies and techniques—discovery, analysis, and quantitation—for workflow-supported org-social networking knowledge management. This section gives the descriptions of the research statuses and surveys related to each of these issues.

In order to carry out the closeness centralization measurement, we need to project the human-centered associative knowledge from a workflow procedure, and transform it to a form of human-centered graph so as to be mathematically analyzed. The performer-flow graph formally represented by the workflow-supported org-social network model is to be proposed with this intention in the paper, and we have addressed this human-centered transformation issue as "workflow-supported org-social networking knowledge discovery issue." This issue can be subdivided into two branches of research approaches—discovery issue and rediscovery issue. The rediscovery issue stems from the workflow mining issue that tries to explore human behavioral knowledge (enacted org-social networking knowledge) from workflow enactment event logs, whereas the discovery issue is related with exploring various human-centered associative knowledge (planned org-social networking knowledge) from the growing pile of workflow models and packages. A typical research publication concerning the rediscovery issue might be [7], in which the authors built a methodology and system to rediscover org-social networking knowledge from the petri-net based workflow enactment event logs. Also, many research groups pointed out the necessity of rediscovering the performer or human behaviors from workflow enactment event logs through those publications, [3,4,8,18], so far. Also, the org-social networking knowledge discovery issue was firstly addressed by the authors' research group through proposing a theoretical framework in [9] and implementing the framework in [10]. In this paper, we have refined the org-social networking knowledge discovery algorithm proposed in [1,9,13], and we efficiently transform the discovered org-social networking knowledge to a form of the performer-flow graph so as to be efficiently applied for the closeness centralization measurements.

After either discovering or rediscovering the workflow-supported org-social networking knowledge, we need to analyze the knowledge and quantitate the analyzed results in order to exert valuable, meaningful, and worth knowledge on workflow-supported organizations. The literature has been trying to solve this analysis issue by two approaches, so far. One is to use the traditional statistical analysis techniques [3], the other is to employ the sophisticated social network analysis techniques already proved in the social science domain and summarily introduced in [5] and [19]. In [3], the authors tried to build a fundamental theory for discovering organizational work-sharing networks, such as role-based organizational work-sharing network and human-based organizational work-sharing network, from a specific workflow procedure, and suggested a new statistical analysis approach for statistically quantifying the degree of organizational work-sharing and collaboration. [5] and [19] elaborated on the social network analysis techniques and the affiliation network analysis techniques, respectively. Note that the affiliation network is a special type of the social network. The authors' research group has employed these sophisticated social network analysis techniques, such as centrality, prestige, and clique techniques, to analyze the workflow-supported org-social networks [13] and affiliation networks [11] explored by the discovery methodologies. In particular, we have been actively adopting the centrality technique in analyzing the workflow-supported org-social networking knowledge, so far. The centrality technique is subdivided into degree-centrality [13], closeness-centrality [12,20], betweenness-centrality [21], and eigenvalue-centrality so as to be elaborately applied into a real organizational world. As one of those efforts, in this paper, we have tried to conceive the algorithmic and procedural framework of closeness centralization measurements and

suggested a theoretical guidance to quantitatively analyze and compare the degrees of closeness and prominence among workflow-performers in enacting a workflow procedure.

5. Conclusion

In this paper, we suggested a theoretical way of discovering, analyzing, and visualizing the closeness centralization measures that are quantitatively expressing the prominency and collaborative behaviors among workflow-supported performers in enacting a workflow procedure. That is, we have built, so far, a theoretical framework for quantitatively and graphically measuring the degrees of closeness centralization among performers assigned to enact a workflow procedure. The proposed framework supports the three procedural phases, discovery, analysis, and quantitation phases, during which they carry out four functional transformations, ICN-to-WsoN, WsoN-to-SocioMatrix, SocioMatrix-to-DistanceMatrix, and DistanceMatrix-to-CCV transformations. We have also developed a series of algorithmic formalisms and verified them through an operational example. As a consequence, we would summarily conclude by showing that the theoretical framework is able to answer to the questions as follows:

- Who is the most important or prominent performer(s) interacting the most tightly with others in enacting a specific workflow procedure?
    - Answer: the performer whom has the highest quantity in the closeness centrality vector or the standardized closeness centrality vector, Maximum($C_C(\emptyset_1)$, ..., $C_C(\emptyset_n)$).
- How near is the most prominent performer to others in a workflow-supported org-social network?
    - Answer: the geodesic distances from the most prominent performer to others in the geodesic distance matrix, *DistanceMatrix*[N, N].
- What is the average distance (or closeness) among performers in a workflow-supported social network? In other words, how quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries?
    - Answer: the index of group closeness centrality, GCC .

At this moment, it is important to emphasize that the proposed framework for the closeness centralization measurements of workflow-supported org-social networks be simply not in theoretical formulas but in algorithmic formulas. Through the theoretical framework, so, we can straightforwardly implement an automatic discovery, analysis, and visualization system for the closeness centralization measurements as well as for workflow-supported org-social networking knowledge management and intelligence. Likewise, as future works, we need not only to elaborate on the functional expansion of the closeness centralization formulas so as for the theoretical framework to handle a group of workflow procedures (or a workflow package) with organization-wide workflow-performers, but also to develop the remainder centrality analysis techniques, like betweenness and eigenvalue centralities, to be applied to workflow-supported org-social networks.

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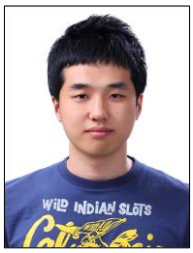

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