Understanding Communication and Collaboration in Social Product Development Through Social Network Analysis

Social media have recently been introduced into the arena of collaborative design as a new means for seamlessly gathering, processing, and sharing product design-related information. As engineering design processes are becoming increasingly distributed and collaborative, it is crucial to understand the communication and collaboration mechanism of engineers participating in such dispersed engineering processes. In particular, mapping initially disconnected design individuals and teams into an explicit social network is challenging. The objective of this paper is to propose a generic framework for investigating communication and collaboration mechanisms in social media-supported engineering design environments. Specifically, we propose an approach for measuring tie strengths in the context of distributed and collaborative design. We transform an implicit design network into an explicit social network based on specific indices of tie strengths. We visualize the process of transforming customer needs to functional requirements, to design parameters, and to process variables using social network analysis (SNA). Specifically, by utilizing a specific index for tie strengths, we can quantitatively measure tie strengths in a design network. Based on the tie strengths, we can map an implicit design network into an explicit social network. Further, using the typical measures (e.g., centrality and cluster coefficient) in SNA, we can analyze the social network at both actor and systems levels and detect design communities with common design interests. We demonstrate the applicability of the framework by means of two examples. The contribution in this paper is a systematic and formal approach that helps gain new insights into communication and collaboration mechanisms in distributed and collaborative design. [DOI: 10.1115/1.4031890]

Keywords: communication and collaboration mechanism, collaborative design, social product development, social networking analysis, tie strength, design network

1 Introduction

As engineering design activities are conducted in an increasingly distributed and collaborative setting, individual designers or design teams at different locations need to communicate and collaborate effectively and efficiently [1–3]. Törnqvist and Larsson [4] described engineering design as “fundamentally a sociotechnical activity” in which engineers gather, process, and share information about customer needs, function requirements, design parameters, and process variables as well as make collective decisions in order to satisfy customer needs. As social media have the potential to enhance communication and collaboration in design, social product development (SPD) has emerged as a new trend to improve traditional distributed and collaborative design processes [5–7]. The objective of SPD is to enhance communication and collaboration in distributed and collaborative design through social computing techniques such as social networking sites and online communities.

Although research related to SPD is in its infancy, companies are piloting social media initiatives to generate business value in the field of design and manufacturing. One of the most well-known industry practices is Yammer [8], a so-called “Facebook for the workplace.” Yammer is a platform designed to streamline communication and collaboration processes by bringing together people, content, and conversations across entire product development processes. Another example is Quirky [9], an industrial design company that utilizes a social media site to bring innovative product ideas to real life. Quirky allows designers and design teams to conduct engineering design modeling and analysis by using cloud-based computer-aided design and finite element analysis tools such as Dassault Systems’ CATIA V6. Meanwhile, Dassault Systems also introduced an online SPD platform, 3DsvWym [10], for sharing design-related information and experiences via commonly used social media tools such as wikis and blogs. In addition, General Electric (GE) and Massachusetts Institute of Technology (MIT) are developing a new crowdsourcing platform [11] to support DARPA’s ongoing adaptive vehicle make portfolio. Their crowdsourcing platform allows a global community of experts to design and rapidly manufacture complex industrial products and systems such as aviation systems by connecting individuals in an online community.

Because of the increasing number of design participants and teams involved in a SPD process, it is crucial to increase the effectiveness and efficiency of design communication and collaboration. The engineering management literature shows that effective and efficient communication and collaboration is one of the most important success factors that affect productivity, lead-time, and costs. Dong [12] reveals that almost all successful product design teams have high levels of communication and collaboration because seamless information sharing supports the creation of a shared understanding of engineering problems between engineers. McKinsey [13] suggests that a “well-connected” design network plays a critical role in the decision-making process of marketing, conceptual, embodiment, and detail design phases based on their recent survey. However, the challenge in understanding communication...
and collaboration mechanisms lies in mapping distributed and collaborative design teams into a network as well as capturing the process of transforming customer needs to functional requirements, to design parameters, and to process variables as shown in Fig. 1.

In the context of engineering design, the purposes of understanding information flow include the following two aspects:

- to analyze the transformation of information among product modules that share design variables [14–19]
- to analyze the transformation of information among individuals or design teams at different design phases (e.g., concept design and embodiment design) [20–22]

This paper is focused on the second aspect because of the sociotechnical nature of engineering design processes as stated before.

While some qualitative studies suggest how human and organizational systems could be restructured to improve productivity [23], only few investigate how information transformation in a design process can be formally modeled and analyzed in a quantitative way. Although SNA has been used to study interfirm relationships of interconnected buyers and suppliers in supply chain management [24], few studies apply SNA in the context of engineering design. In particular, there has been limited study of measuring tie strengths between engineers and mapping initially disconnected individuals and teams in a design network into a social network in the context of distributed and collaborative design. This is largely because (1) there is no formal framework for investigating communication and collaboration mechanisms in distributed and collaborative design; (2) there is a lack of clarification with respect to indices for measuring tie strengths between individuals or design teams; and (3) it is still very challenging to conduct large-scale real-world industrial case studies. The objective of this paper is to address the first two issues as a first step toward understanding communication and collaboration mechanisms in SPD settings.

The remainder of the paper is organized as follows: Section 2 presents a brief overview of communication and collaboration in engineering design as well as related aspects of SNA. Section 3 presents a generic framework for investigating communication and collaboration with a focus on measuring tie strengths and social networks in the context of distributed and collaborative design. Section 4 presents the validation of the framework by means of two engineering design sample problems. In these application examples, we formally map two implicit design networks into two explicit social networks and analyze the social networks using some of the typical measures in SNA such as degree, graph density, betweenness centrality, closeness centrality, and clustering coefficient. In addition, we analyze and interpret the results of our SNA. The results include visualized information flow, network structures, and detected collaboration patterns. Section 5 concludes this paper with a discussion of our research contributions and associated limitations.

2 Literature Review

As previously stated, although some qualitative studies suggest how sociotechnical systems could be restructured to improve the effectiveness and efficiency of communication, only few investigate how complex design networks can be formally mapped into social networks [25–27]. Specifically, the following two research issues have not yet been fully addressed: (1) What indices for measuring tie strengths between designers should be used in the context of design? (2) How can the transformation of customer needs to functional requirements, to design parameters, and to process variables be visualized and analyzed in a formal way? In order to address these issues, this paper builds upon prior work in two areas: (1) qualitative studies in engineering communication and collaboration and (2) SNA in communication and collaboration. We provide a brief review of the related work in the above two areas in Secs. 2.1 and 2.2.

2.1 Communication and Collaboration in Engineering Design. According to Refs. [28–31], the major purposes of design communication include articulating an issue, asking for clarification, eliciting requirements, generating concepts or principles, reverse engineering, requesting information, comparing solutions, and making decisions. Capturing the purposes of design communications can significantly improve the effectiveness and efficiency of design communication by ensuring that engineers know what expected inputs and outputs should be from a communication. With respect to the content or artifacts that are exchanged or shared among individuals or teams, almost all design communications revolve around artifacts including sketches, engineering drawings, computer-aided design files, simulation, finite element analysis files, physical product, calculation, assembly, prototype, and report [31]. According to Henderson [32], among these artifacts, sketches, engineering drawings, and finite element analysis files are perhaps the most fundamental components of engineering design communication in most design contexts. In order to effectively and efficiently support design communication, Gopsill et al. [31] have synthesized the requirements of effective design communication from the review of literature. Some of the most important requirements include: (1) to enable individuals to have ubiquitous access to design-related data, (2) to enable individuals to communicate via multiple channels such as virtual meetings and text messages, (3) to enable individuals to record changes to an artifact as a consequence of a communication, (4) to enable individuals to share text-based descriptions of an artifact, (5) to enable individuals to share electronic references to an artifact, and (6) to enable individuals to solicit responses (e.g., surveys and polls) from one another. However, few studies investigate how to enhance communication and collaboration in engineering design in a quantitative way.

2.2 SNA for Communication and Collaboration. Because social media play an important role in supporting communication and collaboration in a sociotechnical environment, SNA provides both a visual and a mathematical analysis of communication and collaboration relationships between individuals [33,34]. Haythornthwaite [35] introduced SNA as an explicit approach and set of associated techniques for the study of information exchange. Jensen and Neville [36] studied SNA using machine learning and data mining techniques and developed methods for constructing statistical models of network data. Kim and Srivastava [37] presented an overview of the impact of social influence in e-commerce and suggested key issues to focus on, including how to combine social influence data into user preferences, and how to exercise social influence in the context of customers’ purchase decision making. Borgatti and Li [38] discussed the

![Fig. 1 Typical information flow in engineering design processes](Image)
potential of SNA for supply chain management by applying network concepts to both hard (e.g., material and money flow) and soft (friendships and sharing-of-information) types of ties. Gloor et al. [39] introduced a novel set of SNA-based algorithms for mining the web, blogs, and online forums to identify trends and find the people launching these new trends. Lin et al. [40] developed a social networking application, SMALLBLUE, which unlocks the valuable business intelligence of “who knows what?,” “who knows whom?,” and “who knows what about whom?” within an organization. Their goal was to locate knowledgeable colleagues, communities, and knowledge networks in companies. Hassan [41] demonstrated how SNA theory supports the task of designing information technology (IT)-enabled business processes by providing social network metrics for evaluating alternative process designs. These metrics offer better information for process designers who are faced with making IT investment tradeoffs, especially as the process design task is being undertaken. Braha and Bar-Yam [42] analyzed the statistical properties of real-world networks of people involved in product development activities and showed that complex product development networks exhibit the “small-world” property, meaning that the actors can be reached from anywhere by a small number of steps. Despite the literature as mentioned above has investigated product development from a social process perspective, little is known about the potential of the SNA to investigate the information flow and collaboration patterns in engineering design. Especially, the research gap is that few studies are conducted to identify potential metrics for measuring the existence of connections between participants in engineering design. Without formal measures for relationships between individuals in this context, the linkages in social networks are neither rigorous nor accurate.

As part of the SNA, the aim of community detection is to (1) detect organizations or individuals with similar interests and (2) create data structures to handle queries or path searches [43]. The modern science of graph theory has brought significant advances to our understanding of complex networked systems. One of the most relevant features of graph theory is community detection or clustering, i.e., the organization of vertices in clusters, with many edges joining vertices of the same cluster and with comparatively fewer edges joining vertices of different clusters [44]. Girvan and Newman [45] proposed an algorithm aiming at the identification of edges lying between communities and their successive removal, a procedure that after some iterations leads to the isolation of the communities. In this seminal work, the intercommunity edges are detected according to the values of a centrality metrics, and the edge betweenness that expresses the importance of the role of the edges is transmitted across the graph following the paths of minimal length. Identifying clusters of customers with similar interests in the network of purchase relationships between customers and products of online retailers, like Amazon, enables us to set up efficient recommendation systems [46], which better guide customers through the list of items of the retailer and help companies to improve their sales and profitability. Tyler et al. [47] developed a methodology for the automatic identification of communities of practice from e-mail logs by using the betweenness centrality algorithm. This approach enables the identification of leadership roles within the communities. Clauset et al. [48] developed an algorithm for inferring community structure from network topology, which is applied to analyze a large network of co-purchasing data from Amazon.com. The research gap between the SPD and SNA is that few studies investigate the measurement of tie strengths and validate the potential of the SNA on understanding communication and collaboration in engineering design. To bridge the gaps we identified in Secs. 2.1 and 2.2, we introduce a systematic framework for measuring tie strengths and gaining insights into effective and efficient communication and collaboration in SPD settings.

3 A Framework for Investigating Design Communication and Collaboration

In this section, we propose a generic SNA-based framework for investigating design communication and collaboration in SPD settings. The potential users of the framework include systems analysts and users of SPD platforms. A systems analyst monitors the exchange of data between designers participating in a distributed and collaborative design process and evaluates the performance of design communication and collaboration. For example, a systems analyst tracks data such as electronic files (e.g., computer-aided design and finite element analysis files) that are shared among designers. Based on these data, the systems analyst defines an index to measure tie strengths between two individuals or design teams. Based on the values of the index, one can map an implicit design network into an explicit and formal social network. One can further formally analyze the social network by utilizing typical SNA measures (e.g., centrality and cluster coefficient). Then, the social network can be visualized and further analyzed with community detection algorithms that capture the information flow, identify key design participants, also referred to as actors, and detect design communities with common interests. Based on these results, the systems analyst can identify potential communication and collaboration problems through strong and weak ties accordingly. The detailed steps of the SNA framework are presented in Table 1. The key steps of the framework, steps 1 and 3, are discussed in more detail in Secs. 3.1 and 3.2, respectively.

3.1 Measuring Tie Strengths. Social network data are typically gathered through questionnaires and interviews in which the actors are asked to identify the frequency of communication with others as well as mediums of interaction. It is commonly agreed that social network data collected through questionnaires and interviews are not perfectly accurate due to the fact that responses are subjective in nature. Gupte and Eliassi-Rad [49] introduced an axiomatic approach of measuring tie strength between actors in social networks. A list of axioms is used to evaluate specific measures of tie strengths between two actors. We extend that line of work by studying specific indices for tie strengths in the context of distributed and collaborating engineering design. In this section, we review some of the axioms that can help clarify the index that will be used in our application examples in Sec. 4.

AXIOM 1 (ISOMORPHISM): Suppose we have two graphs G and H and a mapping of vertices such that G and H are isomorphic. Let vertex u of G map to vertex a of H and vertex v to b. Then, the tie strength between u and v in the graph G, denoted by T_{G}(u,v), is equal to the tie strength between a and b in the graph H, denoted

<table>
<thead>
<tr>
<th>Table 1 The SNA framework</th>
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</thead>
<tbody>
<tr>
<td>1. Define an index to measure tie strength, that is, to determine whether the ties between the actors exist and to what degree the actors are connected to one another.</td>
</tr>
<tr>
<td>2. Collect raw data about actors and ties between actors for mapping an implicit social network into an explicit social network.</td>
</tr>
<tr>
<td>3. Calculate the measures (e.g., centrality and cluster coefficient) of the explicit social network.</td>
</tr>
<tr>
<td>4. Visualize the social network, capture information flow, and detect key actors and communities with common design interests.</td>
</tr>
<tr>
<td>5. Interpret results and identify potential solutions for enhancing communication and collaboration.</td>
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by $T_S(u, v)$. This relationship can be formally denoted by
$T_S(u, v) = T_S(a, b)$. In the context of engineering design, 
design teams A and B can be represented by two graphs $G$ and $H$, 
respectively. Two engineers in design team A can be represented 
by two vertices $u$ and $v$ in the graph $G$. Similarly, another two 
engineers in design team B can be represented by two vertices $a$ 
and $b$ in the graph $H$. Axiom 1 suggests that the tie strength 
between the two engineers in design team A is equal to the tie 
strength between the two engineers in design team B if $G$ and $H$ 
are isomorphic.

Axiom 2 (Baseline): If there are no events (an event is defined 
as a circumstance participated by a set of individuals for a certain 
purpose), then the tie strength between vertices $u$ and $v$ in the 
graph, denoted by $T_S(u, v)$, is equal to zero. This is formally 
denoted by $T_S(u, v) = 0$. If there are only two actors $u$ and $v$ and 
asingle event they attend, then their tie strength, denoted by 
$T_S(u, v)$, is equal to one. This is formally denoted by 
$T_S(u, v) = 1$. In the context of engineering design, Axiom 2 
suggests that the tie strength between any two engineers in a 
design team is equal to zero if the two designers do not participate 
in any design-related events. This axiom also suggests that the 
tie strength between two engineers in a design team is equal to one 
if there are only two engineers in the design team and they only 
attend one single design-related event.

Axiom 3 (Frequency): All other things being equal, the more 
events common to $u$ and $v$, the stronger the tie strength is 
between $u$ and $v$. In the context of engineering design, Axiom 3 
suggests that the tie strength between two engineers in a design 
team will be greater if they share more common design-related 
events and all other conditions remain the same.

Axiom 4 (Intimacy): All other things being equal, the fewer 
events there are to any particular event attended by $u$ and $v$, the 
stronger the tie strength is between $u$ and $v$. In the 
context of engineering design, Axiom 4 suggests that the tie 
strength between two engineers in a design team will be greater 
if fewer engineers participate in the common design-related 
events they share. In fact, Axiom 4 is a special case of Axiom 2. 
The special case is that the tie strength between two engineers 
in a design team is equal to one if there are only two engineers 
in the design team and they only attend one single design-
related event.

Axiom 5 (Popularity): Consider two events $P$ and $Q$. If 
the number of actors attending $P$ is larger than that of actors 
attending $Q$, then the total tie strength created by event $P$ is more 
than that created by event $Q$. In the context of engineering design, 
Axiom 5 suggests that the total tie strength created by a particular 
design-related event $P$ is more than that created by another one $Q$ 
if more engineers participate in event $P$.

Axiom 6 (Conditional independence of vertices): The tie 
strength of a vertex $u$ to other vertices does not depend on events 
that $u$ does not attend; it only depends on events that $u$ attends. In 
the context of engineering design, Axiom 6 suggests that the tie 
strength of an engineer to others does not depend on the design-
related events that this engineer does not attend.

Axiom 7 (Conditional independence of events): The increase in 
tie strength between $u$ and $v$ due to an event $P$ does not depend on 
other events but on the existing tie strength between $u$ and $v$. In 
the context of engineering design, Axiom 7 suggests that the 
increase in tie strength between two engineers does not depend on 
other design-related events.

Axiom 8 (Submodularity): The marginal increase in tie 
strength of $u$ and $v$ due to an event $Q$ is at most the tie 
strength between $u$ and $v$ if $Q$ was the only event. If $G$ is a graph and $Q$ is a 
single event, then $T_S(u, v) + T_S(u, v) \geq T_S(u, v)$. In 
the context of engineering design, Axiom 8 suggests that the marginal 
increase in tie strength between two engineers due to a common 
design-related event they share is at most the tie strength 
between the two engineers if this event is the only one they attend.

According to Gupte and Eliassi-Rad [49], although plenty of 
generic measures of tie strength exist and each of the axioms is 
fairly intuitive, only some of the well-accepted measures of tie 
strength satisfy all the aforementioned axioms. These measures 
include (1) delta, (2) Adamic and Adar, (3) linear, and (4) max. 
The detailed and formal proofs can be found in Ref. [49]. In 
the following indices, $|P|$ denotes the number of actors in the event 
P. The size of the neighborhood of a vertex $u$ in a graph is denoted 
by $T_S(u, v)$. The tie strength between two vertices $u$ and $v$ in a graph is denoted by 
$T_S(u, v)$.

The delta index defines tie strength as

$$T_S(u, v) = \sum_{P \subseteq \Gamma(u) \cap \Gamma(v)} \frac{1}{|P|}$$

The Adamic and Adar index defines tie strength as [50]

$$T_S(u, v) = \sum_{P \subseteq \Gamma(u) \cap \Gamma(v)} \frac{1}{\log |P|}$$

The linear index defines tie strength as

$$T_S(u, v) = \sum_{P \subseteq \Gamma(u) \cap \Gamma(v)} \frac{1}{|P|}$$

The max index defines tie strength as

$$T_S(u, v) = \max_{P \subseteq \Gamma(u) \cap \Gamma(v)} \frac{1}{|P|}$$

Based on these formally defined tie strengths, we can formally 
map an implicit design network into an explicit social network. The 
following simple example illustrates how we can map a design 
network into a social network based on tie strengths in more 
detail. Table 2 lists five actors and the events they attended. 
These events include sharing a particular digital file (denote by 
P1), making comments on a particular post (denote by P2), participating a particular virtual meeting (denote by P3), a particular 
virtual conference call (denote by P4), and a particular poll 
(denote by P5). Given the dataset in Table 2, we can map an 
implicit design network into an explicit social network (see Fig. 2) 
based on the Adamic and Adar index scores.

### Table 2: Adamic and Adar index scores

<table>
<thead>
<tr>
<th>Actor ID</th>
<th>Actor ID</th>
<th>No. of actors in P1</th>
<th>No. of actors in P2</th>
<th>No. of actors in P3</th>
<th>No. of actors in P4</th>
<th>No. of actors in P5</th>
<th>Adamic and Adar index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.1918</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.1918</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>5.4178</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4.1918</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>5.4178</td>
</tr>
</tbody>
</table>
3.2 Measuring Social Networks. The next step of the framework is to analyze the explicit social network using the following measures at both actor and group levels. We first define some commonly used measures from SNA that help clarify the uses of these measures in the application examples in Sec. 4.

Degree: Degree of a vertex of a network is the number of edges incident to the vertex. In this study, degree gauges how many connections a particular actor possesses. A higher degree reflects more connections that an actor is tied to. In contrast, an actor with a low degree is considered peripheral in a social network. Further, degree also refers to the extent to which an actor influences other actors with respect to the sharing-of-information and decision making, as the actor has more direct connections thereby more likely having more critical information that others may not know about. For instance, a subgroup leader in a distribute design team will more likely have a higher degree as this leader is in a position that calls for meetings, gathers information from other groups to his group members, and delivers information from his group members to other groups.

Graph Density: Graph density is the average of the standardized actor degree indices as well as the fraction of possible ties present in the network for the relation under study. In other words, it measures how many edges in a network compared to the maximum possible number of edges. Graph density takes on value between zero (empty graph) and one (complete graph).

Betweenness Centrality: Betweenness defines the extent to which an actor lies between other actors in a network. This measure takes into account the connectivity of the actor’s neighbors, giving a higher value for actors which bridge clusters. This measure also indicates the number of actors which the actor is connected to indirectly through the direct links [51].

Actor betweenness centrality is defined as

\[
C_b(n_i) = \frac{C_B(n_i)}{(g - 1)(g - 2)/2}
\]

where \(C_B(n_i)\) is the standardized actor betweenness index for \(n_i\), \(C_B(n_i)\) is the actor betweenness index for \(n_i\), \(g\) is the number of actors. The calculation of \(C_B(n_i)\) is discussed in more detail in Ref. [41].

Group betweenness centrality is defined as

\[
C_B = \frac{\sum_{i=1}^{g} [C_B(n^*) - C_B(n_i)]}{(g - 1)^2(g - 2)}
\]

where \(C_B\) is the index of group betweenness, \(C_B(n^*)\) is the largest realized actor betweenness index for the set of actors.

In this paper, betweenness can be viewed as an indication of how much “gatekeeping” an actor does for the other actors. It measures how important the actor is with respect to the flow of information. An actor with high betweenness can control the flow of information as the actor functions as a hub or pivot that transmits information across the network. Further, from the structural position perspective, the actor with high betweenness is more likely one of the key actors in the network as the actor affects the downstream actors’ access to information from upstream actors. For instance, in a design network, the structural position of designers is between market analysts and manufacturing engineers as designers transform function requirements to design parameters. Therefore, designers become a hub between market analysts and manufacturing engineers. If a designer with high betweenness transmits design-related information slowly or delivers some wrong information, the design becomes the bottleneck of the information flow in the network. As a result, the gap in the information flow can easily lead to poor communication and collaboration.

Closeness Centrality: Closeness centrality defines the degree to which an actor is near all other actors in a network. This measure indicates the ability to access information through the grapevine of network members. In other words, the closeness indicates how quickly an actor accesses the information from the network. Closeness centrality is the inverse of the sum of the shortest distance between each actor and every other actor in the network.

Actor closeness centrality is defined as

\[
C_c(n_i) = \frac{g - 1}{\sum_{j=1}^{g} d(n_i, n_j)}
\]

where \(C_c(n_i)\) is the standardized index of actor closeness. \(d(n_i, n_j)\) is the number of lines in the geodesic linking actors \(i\) and \(j\). The details about how to calculate \(d(n_i, n_j)\) can be found in Ref. [51].

Group closeness centrality is defined as

\[
C_C = \frac{\sum_{i=1}^{g} [C_c(n^*) - C_c(n_i)]}{[(g - 2)(g - 1)][(2g - 3)]}
\]

where \(C_C\) is the index of group closeness, \(C_c(n^*)\) is the largest standardized actor closeness in the set of actors.

Clustering Coefficient: Clustering coefficient of an actor is the ratio of number of connections in the neighborhood of an actor and the number of connections if the neighborhood was fully connected. Clustering coefficient identifies how well connected the neighborhood of an actor is. If the neighborhood is fully connected, the cluster coefficient is one. A value close to zero means that there are hardly any connections in the neighborhood of the actor. A higher clustering coefficient indicates a greater cliquishness [51]. In other words, it is the measure of the degree to which nodes in a graph tend to cluster together. In the context of SPD, an actor with low cluster coefficient is more likely one of the group leaders as the neighborhood (group members) of the group leader is generally fully connected.

4 Application Examples

In this section, we present two application examples to demonstrate how the proposed framework can help understand design communication and collaboration mechanism in SPD settings. In our application examples, actors are engineering graduate students in an engineering design class. This class was composed of both on-campus and distance learning students. We required these students to design two mechanical product prototypes in an SPD environment which consisted of a variety of social media tools (e.g., Wiggio, Google Drive, and others). Design activities in these design projects involved the core phases of the systematic design approach by Pahl and Beitz starting from product planning and clarification of task, to conceptual design, embodiment design, and to detail design. The dataset of example 1 was collected in Spring 2011. There were 31 students in a class and the students were divided into two competing subgroups. The dataset of example 2 was collected from the Spring 2012 cohort. There were 39 students in a class and all the students teamed up to form one mass-collaborative group. The projects conducted in the two examples were: (1) example 1—designing a hydroelectric.
footwear (Spring 2011) and (2) example 2—designing a wind-based electricity generation device (Spring 2012).

We selected these application examples for two reasons. First, the two projects were conducted in an SPD environment where a variety of social media tools such as Wiggio, Google Drive, and Dropbox were used to share design-related data. In addition, both of the two projects were conducted in distributed and collaborative settings as shown in Fig. 3.

The on-campus students were located in Atlanta, Georgia, in the U.S.; the distance learning students came from Georgia Tech Lorraine campus in Metz (France), Georgia Tech Savannah campus, Flanders in New Jersey, Fairbanks in Alaska, Phoenix in Arizona, and Milwaukee in Wisconsin. Second, the projects in the two application examples were focused on engineering design problems. The students were also required to build proof-of-concept prototypes to validate their design concepts using 3D printing technology. Therefore, these two design scenarios are very similar to what happens in real-world cases from industry.

4.1 Measuring Tie Strengths. Based on the framework presented in Sec. 3, step 1 is to define a specific index to measure tie strength. Step 2 is to collect raw data about actors and ties that can map an implicit social network into an explicit social network. As stated in Sec. 3.1, according to Gupte and Eliassi-Rad [49], only four indices satisfy all of the axioms. We first measure tie strengths in the application examples using these four indices and then conduct a sensitivity analysis to test the effect of changes in the number of events on the number of edges in the application examples. The \delta, \text{max}, \text{linear}, \text{and Adamic and Adar} index scores for example 1 are shown in the Appendix. Although the index scores for each connection based on these four indices are different, the number of edges is identical. For example, the \delta, \text{max}, \text{linear}, \text{and Adamic and Adar} index scores for measuring the tie strength between actors 1 and 2 are 28.0000, 0.3333, 28.0000, and 176.0559, respectively. Since all of the index scores are greater than zero, an edge is identified between nodes 1 and 2 in the social network. According to the Appendix, the same number of edges is 51. As shown in Table 3, the number of edges we identified remains the same, 51.

According to the result of the sensitivity analysis, we found that these four indices are very robust.

Considering these four indices are all robust measures of tie strengths, all of them are perhaps applicable. However, according to Shannon’s information theory and one of the two axioms in axiomatic design (the information axiom), the most important quantities of information are entropy, the amount of information in common between two random variables. The \text{entropy} is mathematically expressed in the form of common logarithm. Because the \text{Adamic and Adar index} is also defined using common logarithm, this index intuitively includes the quantification of information that is shared in design communication. Therefore, we select the \text{Adamic and Adar index} to measure tie strengths in the application examples. The \text{Adamic and Adar index} scores for example 1 is shown in the Appendix.

4.2 Measuring Social Networks. Based on the index scores in the Appendix, we can map the implicit design networks into two explicit social networks. Step 3 is to calculate the measures (e.g., centrality and cluster coefficient) of the explicit social networks. Step 4 is to visualize the social networks, capture information flow, and detect key actors and communities with common design interests. The major measures we used in these examples include (1) vertices and edges, (2) degree, (3) graph density, (4) betweenness and closeness centrality, and (5) clustering coefficient. We use an SNA tool, NODEXL, developed by Smith’s team at the Microsoft Research [52] to perform steps 3 and 4.

The general network statistics, betweenness centrality, closeness centrality, and clustering coefficient are listed in Tables 4 and 5.

In example 1, eight actors (vertices 1, 4, 8, 15, 16, 20, 24, and 28) are identified as the key actors in the information flow based on their relatively high betweenness scores (see Table 6) in comparison with the average betweenness score: 12.355 (see Table 5). Moreover, two separate groups with eight clusters of actors were successfully detected using the SNA as illustrated in Figs. 4(a) and 4(b). Group 1 was composed of vertices 16–31. Group 2 was composed of vertices 1–15. Four clusters were detected for group 1. The information flow started with the product planning subgroup (vertices 28, 29, 30, and 31), to the concept design subgroup (vertices 24, 25, 26, and 27), the embodiment

![Fig. 3 Geographic locations of participating students](image)

Table 3  Sensitivity analysis of indices for the number of edges in example 1

<table>
<thead>
<tr>
<th>The number of events change by</th>
<th>Delta index</th>
<th>Max index</th>
<th>Linear index</th>
<th>Adamic and Adar index</th>
</tr>
</thead>
<tbody>
<tr>
<td>−5%</td>
<td>51</td>
<td>51</td>
<td>51</td>
<td>51</td>
</tr>
<tr>
<td>−10%</td>
<td>51</td>
<td>51</td>
<td>51</td>
<td>51</td>
</tr>
</tbody>
</table>

---

Transactions of the ASME
design subgroup (vertices 20, 21, 22, and 23), and to the detail
design subgroup (vertices 16, 17, 18, and 19). Similarly, another
two clusters were detected for group 2. Since groups 1 and 2 were
competitive groups, there was no communication between them.
As a result, the two groups were not connected with each other.
In example 2, the general graph metrics and statistics for group
centrality are listed in the right two columns of Tables 4 and 5.
Similarly, eight actors (vertices A, E, J, P, A1, G1, L1, and P1)
are identified as the key actors in the information flow based on
their relatively high betweenness scores (see Table 6) in compari-
on with the average betweenness score: 27.000 (see Table 5).

Table 4  General network statistics in examples 1 and 2 at the
group level

<table>
<thead>
<tr>
<th>Example 1</th>
<th>Example 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graph metrics</td>
<td>Value</td>
</tr>
<tr>
<td>Vertices</td>
<td>31</td>
</tr>
<tr>
<td>Total edges</td>
<td>51</td>
</tr>
<tr>
<td>Maximum vertices</td>
<td>16</td>
</tr>
<tr>
<td>Maximum edges</td>
<td>27</td>
</tr>
<tr>
<td>Graph density</td>
<td>0.109</td>
</tr>
</tbody>
</table>

Table 5  Centrality and clustering coefficient in examples 1 and 2 at the group level

<table>
<thead>
<tr>
<th>Example 1</th>
<th>Example 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centrality</td>
<td>Value</td>
</tr>
<tr>
<td>Minimum betweenness centrality</td>
<td>0.000</td>
</tr>
<tr>
<td>Maximum betweenness centrality</td>
<td>68.000</td>
</tr>
<tr>
<td>Average betweenness centrality</td>
<td>12.355</td>
</tr>
<tr>
<td>Median betweenness centrality</td>
<td>0.000</td>
</tr>
<tr>
<td>Minimum closeness centrality</td>
<td>0.021</td>
</tr>
<tr>
<td>Maximum closeness centrality</td>
<td>0.040</td>
</tr>
<tr>
<td>Average closeness centrality</td>
<td>0.026</td>
</tr>
<tr>
<td>Median closeness centrality</td>
<td>0.025</td>
</tr>
<tr>
<td>Minimum clustering coefficient</td>
<td>0.300</td>
</tr>
<tr>
<td>Maximum clustering coefficient</td>
<td>1.000</td>
</tr>
<tr>
<td>Average clustering coefficient</td>
<td>0.840</td>
</tr>
<tr>
<td>Median clustering coefficient</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 6  Network measures for vertices for examples 1 and 2 at the vertex (actor) level

<table>
<thead>
<tr>
<th>Example 1</th>
<th>Example 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertex</td>
<td>Degree</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>15</td>
<td>4</td>
</tr>
<tr>
<td>16</td>
<td>4</td>
</tr>
<tr>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>24</td>
<td>5</td>
</tr>
<tr>
<td>28</td>
<td>4</td>
</tr>
</tbody>
</table>

Fig. 4  Community detection with Clauset–Newman–Moore algorithm [35]: (a) before community
detection for example 1 and (b) after community detection for example 1
actors are enabled by the SPD systems. The following measures have been found to be important for detecting communities and key actors:

- degree
- betweenness centrality and clustering coefficient at the actor level

One of the main findings based on the results is that the communication and collaboration mechanisms in SPD settings can be visualized and further be analyzed using the SNA. More specifically, the implicit network structures for the two examples were visualized using the SNA tool as shown in Figs. 4 and 5. Based on the visualized network as well as the measures in SNA as shown in Tables 4–6, the structural positions of individual actors in the social networks were revealed, which helps gain insights into the effectiveness of communication and collaboration in engineering design. For instance, in example 1, the actors with ID 1, 4, 8, 15, 16, 20, 24, and 28 as shown in Fig. 4 were identified as the critical players who possess some of the significant design-related information as well as have better control over information flow. In other words, these actors could also be the potential ones becoming the bottleneck of the flow of information in the network. Furthermore, consider group 2 in example 1, for example, the information flow that was detected turns out to be consistent with that of the systematic design method by Pahl and Beitz, starting from the product planning (vertices 28, 29, 30, and 31 in dark blue), concept design (vertices 24, 25, 26, and 27 in light blue), embodiment design (vertices 20, 21, 22, and 23 in dark green), and to detail design (vertices 16, 17, 18, and 19 in light green). As the students are required to use the systematic design method by Pahl and Beitz, the SNA framework is validated to be effective for capturing and measuring information flow in engineering design processes in the context of SPD. Furthermore, individuals with common design activities were also detected. Based on the visualized social networks and clusters, we can effectively identify which designers are conducting similar design activities and where to find the information we may need.

With respect to collaboration patterns, we found that the SPD environments help enhance communication and collaboration among participants as it transformed engineering design collaboration from a conventional sequential pattern into a parallel one as shown in Fig. 5. SPD allows designers to quickly access, edit, and share product design-related information through a set of social media tools. Due to the ubiquitous computing environment in the SPD, the sequence of interaction among individuals or design teams is not always unidirectional from planning, concept design, embodiment design, and to detail design. Instead, it could be...

![Fig. 5 Community detection with Clauset–Newman–Moore algorithm [35]: (a) before community detection for example 2 and (b) after community detection for example 2](image)
multiway interactions as detected in example 2. As shown in Fig.
5, the actors with ID A, E, J, P, A1, G1, L1, and P1 are fully
connected, which means the collaboration pattern is not a sequential
interaction but concurrent information sharing among participants.
Such a multiway interaction or parallel information sharing is
very desirable because different perspectives from different indi-
viduals for the same information can enhance design for X (e.g.,
manufacturability, reliability, and variety).

5 Conclusion

The research described in this paper contributes to the current
body of knowledge in the sense that we introduced a generic
framework for investigating communication and collaboration
mechanisms in SPD settings. Specifically, we measured tie
strengths using four indices that satisfy all of the axioms in SNA
and conducted a sensitivity analysis to test the robustness of the
four indices. Based on the result of the sensitivity analysis, we
observed that all of them are perhaps applicable. Because the
entropy in Shannon’s information theory and axiomatic design is
expressed in the form of common logarithm and the Adamic and
Adar index is also defined using common logarithm, we select the
Adamic and Adar index to measure tie strengths in our examples.
Based on the Adamic and Adar index scores, we transformed
implicit design networks into explicit and formal social networks.
In our examples, we visualized the process of transforming cus-
tomer needs to functional requirements, to design parameters, and
to process variables using SNA. Using the typical measures in the
SNA, we measured the social networks at both actor and systems
levels and detected design communities with common design
activities. This systematic and generic framework helps us gain
new insights into communication and collaboration mechanisms
in SPD settings.

While the framework was validated using two examples, the
limitation of this study is acknowledged as follows. Our applica-
tion examples were not conducted in the context of real industry
environments but in a graduate level engineering design course
where different groups of student play different roles. Although the
projects conducted in the examples were to solve engineering
design-related problems, the working environment can only repre-
sent the real industrial environment to a certain degree. Future
work will focus on conducting real industry case studies.

Appendix: Index Scores in Example 1

<table>
<thead>
<tr>
<th>Actor ID</th>
<th>Actor ID</th>
<th>Delta index</th>
<th>Max index</th>
<th>Linear index</th>
<th>Adamic and Adar index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>28.0000</td>
<td>0.3333</td>
<td>28.0000</td>
<td>176.059</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>28.0000</td>
<td>0.3333</td>
<td>28.0000</td>
<td>176.059</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>6.0000</td>
<td>0.2500</td>
<td>9.0000</td>
<td>59.7947</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>28.0000</td>
<td>0.3333</td>
<td>28.0000</td>
<td>176.059</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>16.8333</td>
<td>0.2500</td>
<td>25.2500</td>
<td>167.7574</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td>16.8333</td>
<td>0.2500</td>
<td>25.2500</td>
<td>167.7574</td>
</tr>
<tr>
<td>8</td>
<td>9</td>
<td>15.6667</td>
<td>0.2500</td>
<td>23.5000</td>
<td>156.1306</td>
</tr>
<tr>
<td>10</td>
<td>11</td>
<td>15.6667</td>
<td>0.2500</td>
<td>23.5000</td>
<td>156.1306</td>
</tr>
<tr>
<td>12</td>
<td>13</td>
<td>17.8333</td>
<td>0.2500</td>
<td>26.7500</td>
<td>177.7232</td>
</tr>
<tr>
<td>14</td>
<td>15</td>
<td>17.8333</td>
<td>0.2500</td>
<td>26.7500</td>
<td>177.7232</td>
</tr>
</tbody>
</table>

Continued

<table>
<thead>
<tr>
<th>Connections</th>
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<tbody>
<tr>
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</table>

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