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The Impact of Cognitive Style on Social Networks in On-Line Discussions

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ABSTRACT

With the rise of e-Learning in engineering education, understanding the impact of individual differences on the ways students communicate and collaborate on-line has become increasingly important. The research described here investigates the influence of cognitive style on the interactions within student social networks in an on-line learning environment, with a particular focus on student engagement, patterns of communication, and the self-directed creation of sub-groups (i.e., cliques). The Kirton Adaption-Innovation Inventory (KAI) was used to assess cognitive style, and UCINET software was used to analyze the interactions of two cohorts of Systems Engineering students throughout a series of asynchronous on-line discussion forums across two graduate-level courses. Among the findings, the highly heterogeneous style composition of the cliques formed by the students suggests that e-Learning environments may mask cognitive differences that have been shown to create conflict in face-to-face student interactions. Links between cognitive style, expansiveness, influence, leadership, and students' choices between resident and on-line programs are also discussed.

Keywords: cognitive diversity, Kirton Adaption-Innovation Inventory (KAI), on-line education, social network analysis (SNA), leadership

INTRODUCTION

The work described here lies at the juncture of two rising themes in engineering education research: (1) the impact of individual differences on student performance, and (2) the role of social networks in on-line environments. The study of individual differences among engineering students has expanded over the past two decades, with key contributions made in several areas, including students' learning styles (characteristic ways of taking in and processing information), approaches to learning (surface, deep, and strategic), and intellectual development levels (attitudes about the nature of knowledge and how it should be acquired and evaluated) [7]. In recent years, the investigation of engineers' cognitive styles (characteristic ways of solving problems) has also gained attention, with studies conducted in both academic and corporate settings [12,13,18,19].

The study of social networks also has a rich history that continues to develop across multiple domains [10, 24, 30]. Set in the context of collaboration, advice giving, problem solving, and other forms of human interaction, this research is providing insight into how social networks form and function, as well as the patterns of communication and power structures that emerge as a result of these interactions. The study of interaction behavior and network formation in on-line social networks is becoming ever more relevant as virtual business operations and global teams become increasingly common, resulting in growing interest in these topics [5,11,23,25,31]. Within this domain, the social networks of engineering students engaged in e-Learning are of special interest to engineering educators.

The aim of this research is to integrate these two themes by exploring the impact of cognitive style on the structure and operation of students' on-line social networks through an investigation of their behavior in on-line discussion forums (i.e., who interacts with whom, how often, in what ways, etc.). On-line discussions are often an integral part of e-Learning experiences and serve as graded activities within many on-line courses. If cognitive style has a predictable influence on the ways in which students approach and manage these discussions, then in addition to shedding light on the general relationship between cognitive style and social networking, this work may also help educators guide and evaluate the performance of engineering students engaged in e-Learning activities.

THEORETICAL AND PRACTICAL FOUNDATIONS

Cognitive Diversity: The Level-Style Distinction

In describing the cognitive diversity of individuals, a number of fundamental variables are commonly used [8,18,21,28,32]; cognitive level and cognitive style are two of these. Placing these variables in the familiar context of problem solving, *cognitive level* refers both to an individual's inherent potential capacity (such as intelligence or talent) and their manifest capacity (such as knowledge or learned skills) for solving problems. That is, cognitive level describes "by/with how much" one solves problems. In contrast, *cognitive style* refers to "the preferred way" in which a person solves problems, or, as Kirton states, "the stable, characteristic, and preferred manner in which an individual responds to and seeks to bring about change" [18]. Messick [21] contrasts the properties of cognitive styles and intellectual abilities (i.e., cognitive levels), noting that "abilities are seen as unipolar, whereas cognitive styles are typically conceived to be bipolar". That is, abilities range from none (or a little) to a large amount, while cognitive styles range from one extreme (or pole) to a different, contrasting extreme (see Figure 1).

As shown in Figure 1, both cognitive level and cognitive style have multiple dimensions, each of which may be assessed using an appropriate psychometric instrument. For example, cognitive level can be measured in terms of potential capacity through intelligence or aptitude tests, while manifest capacity may be assessed in terms of (e.g.) skills, knowledge, and/or expertise—with all of these varying in terms of both type (e.g., mathematics, engineering, economics) and amount/degree (e.g., novice to expert). When it comes to cognitive style, some well-known dimensions include Introversion-Extraversion [6,20], Left-Right Hemisphere Style of Thinking [28], and Adaption-Innovation [17,18]. Various researchers have demonstrated the independence of cognitive style and cognitive level (see, e.g., Kirton [18], Table 5, p. 156), as well as the stability of cognitive style over one's lifetime [4,18]. As a result, individuals at every level can be found all along the continua of style, and every position on a style continuum is also represented at every level—whichever

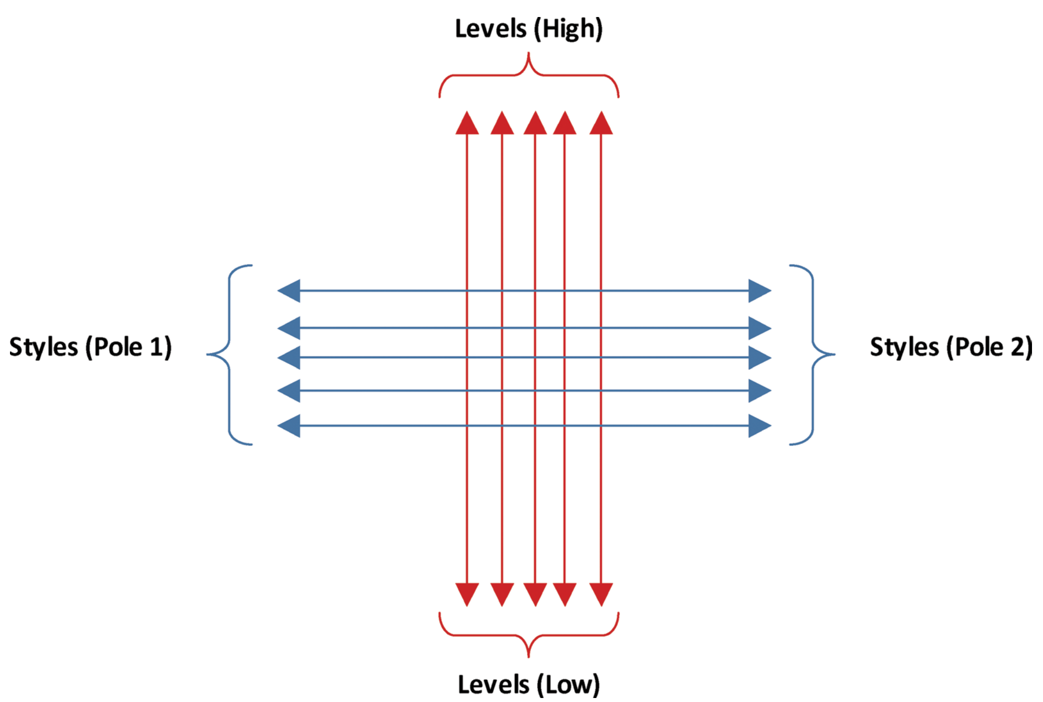

Figure 1: Multiple dimensions and independence of cognitive level and cognitive style.

particular level and style dimensions are concerned. This level-style distinction is critical, as differences in style are often misinterpreted as differences in level, with those of different styles often deemed (mistakenly) to be "inferior" in some way.

Cognitive Style: Adaption-Innovation and *KAI*®

Both Felder and Brent [7] and Tiedemann [27] stress the importance of using reliable, well-validated, and effective psychometric instruments in educational research. Kirton's Adaption-Innovation Inventory (KAI) meets all these requirements in its assessment of cognitive style [17,18]. Initial validation of KAI was based on six general population samples across 10 countries (including the U.S.) with a total of approximately 3000 subjects; the internal reliabilities range between .84 and .89, with a mode of .87 [18]. Additional supporting data (derived from the KAI Manual) relating to the instrument's development, validation, and testing may be found in Appendix 6 of [18]. In addition, over 300 scholarly papers and more than 95 graduate theses have been published in support of the inventory and its underlying theory. Since the initial validating studies, KAI has been applied across many domains, including engineering, education, leadership, marketing, and management, to name a few. It also does its job compactly and efficiently, requiring only 15–20 minutes to complete its 32 scored items; each response is assigned a value using a 5-point scale. The inventory is designed for adults with work experience, but it has been used with bright children as young as 13 with good results.

As shown in Figure 2, a person's KAI score will fall within a range of 32 to 160 (theoretical mean: 96), with a score of 32 representing the theoretical limit of highest Adaption, and a score of 160 representing the theoretical limit of highest Innovation. In practice, scores typically fall between 45 and 145. Within KAI's wide range, the "just noticeable difference" (JND) between two individuals is quite small (10 points), with larger differences requiring increasing amounts of care and attention to avoid miscommunication. At this point, it is also important to note that cognitive style is not the same as behavior. While behavior is flexible, cognitive style has been shown to be fixed early in life and is highly resistant to change [14,18].

For large general populations, the distribution of KAI scores forms a normal curve with an observed mean close to 95 (± 0.5) and a standard deviation of (circa) 17 for all samples [18]. In terms of gender differences, women are (on average) about one third of a standard deviation more adaptive than men, with women's KAI scores normally distributed around a mean of 91, and men's KAI scores normally distributed around a mean of 98. To date, no culture differences have been found in the large sample studies. Smaller groups can be predictably different from general populations, depending on their problem-solving orientation, and may exhibit skewed distributions about different means.

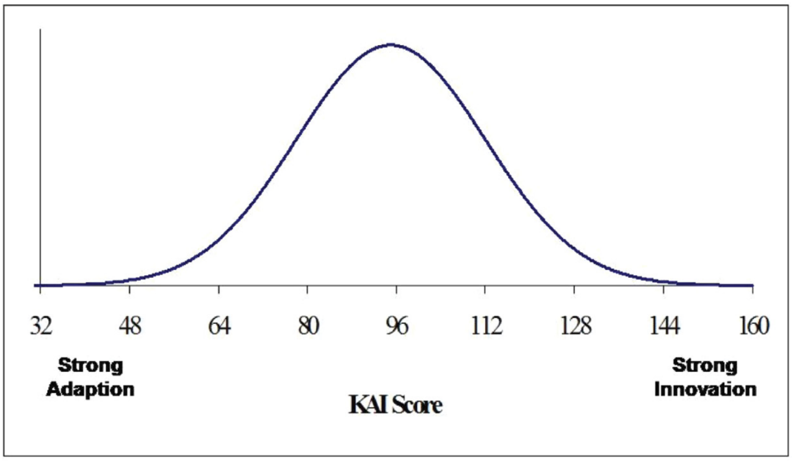

Figure 2: The Adaption-Innovation (A-I) continuum with typical KAI distribution for a large, general population.

From a practical standpoint, the key distinction between more adaptive and more innovative individuals relates to their preferred manner of managing structure, whether that structure is "personal" (e.g., groups, teams, cohorts) or "impersonal" (e.g., rules, guidelines, constraints). In general, individuals who are *more adaptive* prefer to operate with <u>more</u> structure and with more of that structure consensually agreed, while individuals who are *more innovative* prefer to operate using <u>less</u> structure and are less concerned with consensus around that structure [18] (see Figure 3).

In addition to these broad differences in cognitive preference, an individual's A-I cognitive style can also be analyzed in terms of three sub-factors, with their corresponding sub-scores: Sufficiency of Originality (SO), Efficiency (E), and Rule/Group Conformity (R/G) [18]. The first of these, Sufficiency of Originality (SO), helps highlight differences between individuals in their preferred ways of working with ideas. For example, when generating ideas, the more adaptive prefer to offer a manageable number of novel options that are readily seen to be relevant, acceptable, and aimed at immediate and efficient improvements to the current system (structure, solution, process, etc.). In contrast, the more innovative prefer to offer numerous novel options, some (even many) of which may not be seen as immediately relevant to the current problem and/or may be difficult to implement efficiently as part of the current system.

It is important to note that an adaptive individual's preference for offering "a manageable few" ideas does <u>not</u> mean they *cannot* offer more. Rather, their prudence reflects a cognitive strategy aimed at supporting and refining the current system of operation through solutions that are more likely to succeed <u>within</u> its enabling structure. The cognitive strategy of the more innovative, on

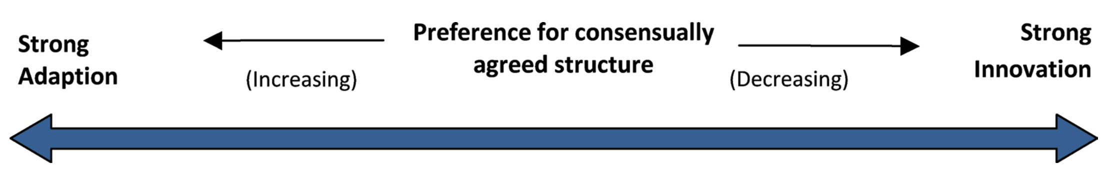

Figure 3: A-I cognitive style and preference for structure.

the other hand, is aimed at altering the current system in more radical ways *as a start*, in order to pursue solutions that are more likely to succeed outside the prevailing structure (which the more innovative tend to see as more limiting than enabling). In the end, cognitive level is the ultimate limit on the number and complexity of ideas an individual can produce, whatever their cognitive style may be.

The second sub-factor, Efficiency (E), reflects an individual's preferred method of operation in tackling problems. For example, the more adaptive prefer to define problems and their solutions carefully and tightly, paying closer attention to details while searching methodically for relevant information. They also tend to be more organized and meticulous in their operations, characteristics which may be perceived as "obsessive" by their more innovative peers. In contrast, the more innovative often loosen or reframe the definition of a problem before they begin to resolve it, paying less attention to detail and taking a less careful approach as they search for and carry out their solutions. Their efforts may be viewed as "sloppy" or "incomplete" by their more adaptive counterparts.

The final sub-factor, Rule/Group Conformity (R/G), reflects differences in the ways individuals manage the structures (both personal and impersonal) in which their problem solving occurs. For example, the more adaptive generally see standards, rules, traditions, and guidelines (all examples of impersonal structures) as enabling and useful, while the more innovative are more likely to see them as limiting and irritating. When it comes to personal structures (e.g., teams, partnerships), the more adaptive tend to devote more attention to group cohesion, while the more innovative are more likely to "stir up" a group's operations (intentionally or not).

All these (and other) style-related individual differences have been shown to create tension and conflict within heterogeneous teams (i.e., teams composed of individuals whose A-I styles differ by more than 10 points) if they are not managed well [3,9,18]. Such challenges can surface whether the team is focused on developing a specific, shared deliverable [3,18] or engaged in a collaborative activity designed to facilitate information exchange and knowledge construction within the group [9,18]. Even so, it is important to realize that a wide range of cognitive diversity may be required to solve the particular complex problems facing the team. In contrast, homogeneous style teams (i.e., teams composed of individuals whose styles differ by 10 points or less) tend to experience fewer interpersonal difficulties, but they also tend to be less effective at solving a wider diversity of problems [14]. This is a good example of Kirton's "Paradox of Structure" in the context of teams [18]—i.e., the same cognitive and social structures that enable the team will also limit it.

Social Network Analysis in Higher Education

Social network analysis (SNA) is a widely used methodology that supports both mathematical and graphical analyses of human relationships [10,24,30]. SNA has been widely utilized to study the structure of social networks across numerous domains, including the social sciences, politics, business, communication, and information science. Through SNA, a variety of metrics can be computed based on the interactions between individuals (actors) in a communication network. Centrality metrics are commonly used to determine an individual's role, position, and relative influence within a given network. In particular, *out-degree centrality* is a measure of how influential an actor is in terms of their "expansiveness", while *in-degree centrality* may be used to reflect a person's prestige or popularity within the group. Other individual metrics include *closeness centrality* (related to how quickly a person can interact with others) and *betweenness centrality* (the extent to which an actor serves as an information "broker" within the group). Still other SNA metrics measure attributes of the group's social structure as a whole (e.g., *network density* reflects the overall level of engagement in the network) or in part (e.g., identification and characterization of clusters, cliques, and other subgroups). Network density helps researchers understand the kinds of ties that exist between actors within a particular social structure, the speed at which information diffuses among the actors, and the degrees of cohesion, trust, and social capital within the group. For a comprehensive overview of social network analysis, see [10,24,30].

Given the growing importance and expanding role of on-line education in today's society, SNA is emerging as a powerful tool for gaining important insights into student interactions and knowledge exchange within on-line learning environments. While instructors in resident classroom settings can readily observe the level of student participation, as well as the quality of student engagement in classroom activities, similar assessments are often difficult to make in on-line educational settings. SNA can offer on-line educators a perspective on classroom activity that extends beyond simply monitoring the number of postings a student makes. It is being applied increasingly to assess the patterns of interaction in on-line discussions, as well as to provide insight into the manner in which knowledge is constructed in these educational communities [1].

Numerous studies have demonstrated the applicability of SNA as a means to evaluate the social roles that emerge during asynchronous on-line discussions [5,11,23,31,33]. SNA can reveal not only the most prolific and the most consulted students, but it can also provide insight into more complex aspects of social dynamics within the on-line class by identifying those students who assume roles as bridgers or mediators between their classmates. For example, Erlin, et al. [5] used SNA to identify the most influential participants in asynchronous on-line discussions (e.g., those with high out-degree and in-degree metrics), as well as students who appeared as social (classroom) isolates (e.g., those with low in-degree and out-degree metrics). In addition, SNA was used to identify students who assumed bridging roles, as well as those who served as "gatekeepers" to regulate the flow of information in the forum (e.g., those students who possessed high closeness and/or betweenness metrics). Russo and Koesten [23] reported that the centrality and prestige of students in an on-line graduate class, as determined by out-degree and in-degree centrality metrics, respectively, served as effective predictors of cognitive learning outcomes (e.g., comprehension and retention of knowledge).

In addition to providing insights into student social roles and positions, SNA is also beneficial for evaluating the patterns of social interactions and information exchange that occur within the class as a whole. Two prominent types of interactions have been observed to emerge during asynchronous on-line discussions in distance learning environments; specifically, social networks have been shown to exhibit either a star or an interconnected web pattern [33]. The star pattern reflects a highly centralized network, in which a single individual (or a few individuals) serve as the focal point(s) of centrality and power through which much of the communication will pass. This pattern often reflects an instructor-led forum, in which the instructor controls the direction of the discussion. In contrast, interaction patterns that manifest themselves as interconnected webs reflect multiple points of centrality within the forum activity of the network (e.g., multiple people guide the discussion threads). The interconnected web pattern of interaction reflects more extensive information exchange and debate amongst the students. Zhu [33] reports that discussions that follow the interconnected web pattern of interaction may be more conducive for collaboration and knowledge construction.

In asynchronous learning environments, the format and design of the forum itself was found to be critical for promoting information exchange and facilitating knowledge construction within the on-line class. Aviv, et al. [1] reported that a high level of critical thinking and the formation of cohesive cliques within the on-line class were only attained when discussion forums were designed with a formal, well-structured, and closed format. In open, non-structured discussion forums, the level of cognitive activity was low, with little knowledge construction taking place, and few cliques formed within the class. In the present study, the on-line discussion forums were designed with a well-structured, closed format in order to stimulate information exchange that would support the formation of an interconnected web pattern of interaction.

Several researchers have evaluated the motivational factors that may influence the patterns of interaction that emerge in on-line educational discussion forums. Sundararajan [26] reported that respect (real or perceived) and social influence within student social networks in Computer-Supported Collaborative Learning (CSCL) environments were important motivational factors that compelled students to participate in class discussions. In this context, respect within a student social network may be linked to a student's past achievements or may be attained through collaborative interactions. Forums that encourage sustained dialogue and continued contact among class members were also found to be extremely important for the formation of strong network ties [11]. Additionally, high interaction frequency among graduate students in on-line learning environments has been found to be strongly associated with the students' perceived sense of community [25].

Recently, researchers have begun to address the impact that individual psychological differences have on participation and patterns of communication in social networks. For example, psychological attributes such as Extraversion and Neuroticism have been shown to impact the structure of an individual's local social network [16,29]. Kalish and Robins [16] found a positive correlation between Extraversion and the density of network connections (i.e., more extraverted individuals had a greater propensity to form larger, denser networks), and Totterdell, et al. [29] reported similar results. Kalish and Robins [16] also found that individuals who scored higher on Neuroticism created networks with many structural holes (e.g., as evidenced by decreases in strong tie network closure), which may reflect a lower level of trust in others. In the present study, we will build on these and other related efforts by examining an aspect of individual differences that has not yet been addressed in relation to social network formation and interaction—namely, the relationship between the Adaption-Innovation dimension of cognitive style and the dynamics of students' on-line social networks.

RESEARCH METHODS

In this section, we begin with a description of the student sample and the context in which data were collected. This is followed by a discussion of the data collection and aggregation procedures.

Student Sample

The sample consisted of two cohorts of Systems Engineering students enrolled in a 2-year, fully on-line Master's degree program (see Table 1). Each cohort was observed in 11 discussion forums across two 7-week courses focused on problem solving (referred to as PS I and PS II) [12]. Thus, this analysis covers on-line discussions within each cohort (across two different courses taught by the same instructor) and across the two cohorts (within the same set of courses). Since active participation in on-line discussion forums is important for enhancing the e-Learning experience, students were graded (individually) on their participation in the forum activities. For each discussion forum,

Instructor	Cohort	Course	No. of Students		No. of Discussion Forums
A	1	PS I	27	17 male 10 female	5
		PS II	28	17 male 11 female	6
B	2	PS I	27	23 male 4 female	5
		PS II	24	21 male 3 female	6

Table 1: Overview of student sample and course details.

students were required to make at least one original posting in response to a specific set of questions and a minimum of one substantive response to any classmate's posting.

Data Collection and Processing

To assess cognitive style, the KAI was administered by a certificated practitioner to each student at the beginning of the first course (PS I) as part of the regular course curriculum. The certification process for KAI (managed by the UK-based Occupational Research Centre [22]) is carefully controlled to preserve the integrity of the instrument and prevent its misuse. The KAI is not self-scorable, but an electronic version of the instrument is currently under development that will feature automatic scoring. Confidential feedback was provided to each student individually; each cohort also participated in on-line exercises in which they were encouraged to share and discuss their scores with their classmates. Experience with this process (both resident and on-line) shows that students are generally eager to share their scores and corresponding insights, as long as a safe environment has been established and once they clearly understand the value found in all cognitive styles across the A-I spectrum [12]. KAI total scores and sub-scores were calculated for each student and across the cohorts (as separate groups). These results will be reported in the next section.

Social network analysis (SNA) data were collected from transcripts of the threaded discussion forums, which were posted asynchronously through an on-line course management system. The forums were designed to provide students with a venue to discuss and debate the impact that cognitive diversity has on various aspects of problem solving and to gain an appreciation for how differences in cognitive level and style can be leveraged to improve team performance. Selected case studies from the literature and/or thought-provoking questions served as catalysts for the weekly forum discussions. Specific topics included how common misconceptions about creativity can lead to practical difficulties at work, the impact and management of cognitive gaps within a team, and how individuals develop effective strategies for managing change in the midst of solving complex problems. Within the context of these discussions, students were encouraged to explore the ways in which cognitive diversity has manifested itself within their own personal and professional collaborations.

To preserve anonymity, each student was assigned a code number, with their corresponding KAI score listed in parentheses behind it (see Table 2, column 1). For each forum transcript, all interactions were recorded in a *forum adjacency matrix* to show "who replied to whom", as well as the number of replies made by each student to each classmate's thread. Then, for each course within a cohort, the interaction data were compiled for all discussion forums and aggregated in a *course adjacency matrix*. These four course adjacency matrices comprised the "database" for the SNA calculations and interpretations in this study.

A portion of the course adjacency matrix for PS I (Cohort 2) is shown in Table 2 for illustration, where (as an example) Student 27 (KAI=127) responded to Student 8 (KAI=82) a total of 4 times

Cohort 2, PS I	1 (50)	2 (56)	3 (67)	4 (71)	5 (78)	6 (78)	7 (79)	8 (82)	9 (88)	10 (88)	11 (89)	12 (89)	13 (90)	14 (91)	15 (92)	16 (92)	17 (94)	18 (95)
1 (50)							1	1	1					1		1		1
2 (56)						2						1						
3 (67)					3			1		2					2			1
4 (71)											1			1				1
5 (78)		2	1	1				1					1	2	1	1		
6 (78)	1	1			2									1				
7 (79)					1			1	1	2			1				1	1
8 (82)	1	1												2	2			
9 (88)	1									1	1				2			1
10 (88)			1					1	1							1		
11 (89)				1											1		1	2
12 (89)	1	2		1					1					1			1	
13 (90)	1	1																
14 (91)	1	1		1				1					1		1			1
15 (92)			1		2			1									1	
16 (92)					1			1		2		1						1
17 (94)							1	1	1	1					1	1		
18 (95)				1				1		2					1		1	
19 (98)					1				1								2	
20 (99)									2	1	1				1			1
21 (100)	1			1		1			1									
22 (102)							1	1		1								1
23 (109)	1				2	1	2		1	1	1		2	2	1			2
24 (111)					1	1		1			1			1			1	2
25 (115)		3	1		1							1	1					
26 (121)						1				1					2			
27 (127)		2	1	1	1			4		2				2			2	

Table 2: Portion of the course adjacency matrix for PS I (Cohort 2).

during the 5 discussion forums in that course. Therefore, each column of an adjacency matrix contains the in-degree data for the individual at the head of that column; each row contains the out-degree data for the individual at the head of that row [24]. This results in an asymmetric data structure, which impacts the selection of SNA techniques. The four course adjacency matrices were first examined visually to see if any obvious communication patterns could be discerned. Although it may be possible to identify students who are particularly engaged or isolated through such observations, the size and relative sparseness of these matrices made it difficult to characterize communication patterns systematically through visual inspection. Formal mathematical analysis of these data will be discussed in the next section.

RESULTS AND DISCUSSION

Cognitive Style Diversity within the Sample

In discussing the cognitive style diversity of the sample, we will begin with the KAI total scores and then move to a sub-score analysis. The KAI total score distributions for both cohorts are shown in Figure 4. A wide range of cognitive style diversity was found in each case (KAI total score ranges of 66 and 77 points, respectively), with both cohort means close to 90. These results were compared with KAI total scores collected from the general population (by Kirton and others; see [18] for details), as well as total scores collected from resident sections of PS I (see [12] and [15]). In

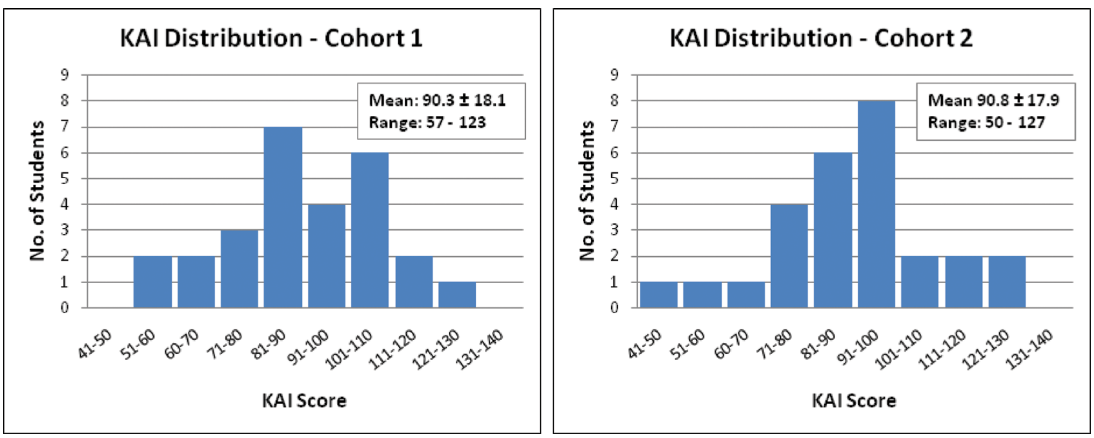

Figure 4: KAI total score distributions for both on-line cohorts.

its resident form, PS I routinely attracts students enrolled in Systems Engineering, Software Engineering, and Information Science, enabling a good comparison between the on-line cohorts (which were comprised of Systems Engineers only) and students from several different disciplines. These data are all presented in Table 3.

In comparing these samples, it is useful to note that the "just noticeable difference" (JND) between two groups (as measured between their KAI means) is 5 points [18]. Thus, we see that both on-line cohorts were (on average) slightly more adaptive than the general population. In addition, they were also more adaptive than the resident samples of Systems Engineers, Software Engineers, and Information Science students, respectively, with some of these differences being quite noticeable. Although more data will need to be collected to be certain of the statistical significance of these results, they do raise some interesting questions about the choices students make in choosing a degree program. For example: is cognitive style a factor when students choose between on-line and resident programs? Do more adaptive students find on-line programs more appealing (on average) than their more innovative peers (as the trend in means in Table 3 might suggest), and if so, in what ways? What impact would such a style skew have on the cognitive climates of the resulting cohorts? As more data are collected, these questions will be investigated further.

Sample	Size (N)	KAI (Total Score) Range	KAI (Total Score) Mean	SO Subscore Mean	E Subscore Mean	R/G Subscore Mean
On-line Cohort 1	27	57 - 123	90.3 ± 18.1	40.1 ± 8.7	15.7 ± 5.1	34.4 ± 8.3
On-line Cohort 2	27	50 - 127	90.8 ± 17.9	41.6 ± 9.8	16.2 ± 3.9	33.0 ± 8.1
General Population [18]	562	45 - 145	95 ± 17.9	40.8 ± 8.9	18.8 ± 5.6	35.4 ± 8.6
Systems Engineers (resident) [15]	120	53 - 138	96.3 ± 18.6	42.68 ± 8.6	18.08 ± 8.6	35.5 ± 8.6
Software Engineers (resident) [15]	63	54 - 143	97.3 ± 16.1	42.2 ± 8.6	18.4 ± 4.6	36.7 ± 6.8
Information Scientists (resident) [15]	117	64 - 136	100.03 ± 17.1	44.8 ± 8.2	18.5 ± 4.8	36.7 ± 7.9

Table 3: KAI comparison between on-line cohorts and other populations.

Next, we compared KAI sub-score distributions for the on-line cohorts with those obtained for the general population and those for the resident students (again, see Table 3). In this case, the SO sub-score means for the on-line students were on par with the general population, while the E and R/G sub-scores were both skewed (on average) towards Adaption, with the skew in the E sub-scores being the more noticeable of the two. Again, while these results are not statistically significant, they highlight some intriguing lines for future investigation. This particular on-line degree program is highly structured in its operations, with students moving through the course sequence in "lock step", with limited breaks. This extra bit of programmatic efficiency is bound to be more appealing to those with a matching cognitive preference, which may be reflected in an adaptively skewed E sub-score. It is also interesting to note that many of the students enrolled in this program work in environments that favor structured processes and routines (e.g., the military, defense contractors), where an adaptive skew in Efficiency might be a useful cognitive characteristic to have.

Finally, cognitive style statistics were compiled for the two on-line cohorts based on gender; Table 4 shows these results. Here, it is clear that wide ranges of cognitive style were present for both men and women, with relatively similar means between the male and female groups, and almost identical means across the male groups.

Network Density—a Measure of Student Engagement

Quantitative analysis of the interaction patterns in the asynchronous on-line discussion forums was performed using UCINET analytical software [2] to generate network density and centrality metrics. In an e-Learning context, the *density* of a social network is defined as the ratio of active student-to-student ties within the network to the maximum possible number of ties. Here, network density was used to assess the overall connectedness or engagement of the students within each course. The maximum possible number of ties for the students in each course is $N \times (N-1)$, where N is the number of students in that course. As an example, in Cohort 2, PS I, there were 27 students, resulting in $(27 \times 26) = 702$ maximum possible ties in the asymmetric network. A network density of 0.3419 for this course indicates that 240 or 34.19% of these ties were present (i.e., active). Similar calculations were made for each course; they are reported in Table 5.

Our analysis across the cohorts and courses shows that network density (i.e., overall connectedness) increased by at least 10% for both cohorts from the first course to the second; with such similar cognitive style profiles, it was not possible to tell whether style had an impact in this regard. The increased density may be the result of a general increase in familiarity within each cohort as they progressed through the on-line degree program and/or increased comfort and interest in discussing the subject matter (i.e., problem solving) as the students learned more about it. In either case, it

Cohort	Class	N	KAI Mean - Males	KAI Range
1	PS I	17	90 ± 17	61 - 123
	PS II	17	90 ± 17	
2	PS I	23	90 ± 17	50 - 127
	PS II	21	90 ± 18	

Cohort	Class	N	KAI Mean - Females	KAI Range
1	PS I	10	90 ± 21	57 - 116
	PS II	11	93 ± 21	
2	PS I	4	93 ± 24	67 - 115
	PS II	3	85 ± 23	67 - 111

Table 4: KAI total score means and ranges for both cohorts sorted by gender.

Cohort	KAI Mean	Course	Density
1	90.3 ± 18.1	PS I	0.3219
		PS II	0.463
2	90.8 ± 17.9	PS I	0.3419
		PS II	0.4475

Table 5: Network density across cohorts and courses.

seems an encouraging result for educators who may be concerned about students building rapport within their e-Learning communities.

Degree Centrality—Connections and Isolation in the On-line Environment

Degree centrality metrics provide an important means of assessing the linkages between students within an on-line community. When working with directed data (as in this study), it is important to calculate both in-degree and out-degree centrality metrics, since the relationship between two students in the direction A-to-B is not necessarily the same as B-to-A. Students with high *out-degree* values send many ties to others and may be viewed as more expansive "data sources". High out-degree values may also reflect an individual's greater degree of influence within the network. In contrast, students with high *in-degree* values receive many ties from other students and may be viewed as "data sinks". High in-degree values may also reflect students who are more popular or prestigious within the network.

UCINET was used to analyze both the in-degree and out-degree centrality metrics for each cohort. In addition, UCINET's univariate statistical analysis tool was used to determine the normalized mean for each student's in-degree and out-degree centrality metrics across the discussion forums within each course. The complete out-degree and in-degree results for Cohort 2 are shown in Table 6 as an example, along with the KAI total score and gender of each student in the cohort. As an example of out-degree centrality, Student 23 (KAI=109) had an out-degree value of 20 across all five discussion forums in PS 1. In a cohort of 27 (i.e., with 26 peers), this results in a mean out-degree centrality metric of (20 ÷ 26) = 0.769 for that student. This student had an in-degree value of 8 across the same five discussion forums, which results in a mean in-degree centrality metric of (8 ÷ 26) = 0.308.

Within each cohort, both the in-degree and out-degree centrality values varied widely. The lowest and highest out-degree values observed across both cohorts and courses were 4 and 29, respectively; the lowest and highest in-degree values were 0 and 22. Note that an in-degree value of 0 indicates that the individual received 0 ties from the remaining students—i.e., the individual was effectively isolated from the rest of the cohort, in that no one responded to their postings. In this study, only one student fell into this category (Cohort 2, Student 22—see Table 6), with an in-degree value of 0 in PS I. It is interesting to note that this same student had a low out-degree value (6) in this course, and their metrics were only slightly higher (in-degree=4, out-degree=8) in PS II. Clearly, such a communication pattern should be investigated further by the instructor.

The in-degree and out-degree centrality metrics were analyzed with respect to cognitive style and gender to determine whether particular patterns of communication could be linked to either variable. No consistent pattern emerged to suggest that there was any relationship between in-degree or out-degree centrality and gender. Regression analyses were performed across both cohorts and courses to determine whether there was any correlation between KAI scores and in-degree/out-degree metrics. As shown in Figure 5, there was no correlation between cognitive style and in-degree centrality; that is, cognitive style did not appear to impact a student's perceived prestige or popularity within the network.

In terms of out-degree centrality, there was a slight positive trend for students with more innovative cognitive styles to have higher out-degree scores, but this correlation was not significant (see Figure 6). Since multiple variables are likely to influence a student's level of engagement in an on-line discussion forum (e.g., motivation, time constraints, interest in the discussion topic, etc.), this result is not surprising. However, the suggestion of a tendency for more innovative individuals to interact with more of their classmates is still interesting from several perspectives. Given the fact that innovative individuals characteristically offer a greater number of ideas, and given a modest correlation between Innovation and Extraversion (identified in the literature [18]), it is plausible that students with more innovative styles may have a greater propensity for reaching out to a larger proportion of their network (e.g., have greater expansiveness) than students with more adaptive styles.

Student	KAI	Gender	Out-Degree		In-Degree	
			Value	Mean	Value	Mean
1	50	M	9	0.346	8	0.308
2	56	M	7	0.269	13	0.5
3	67	F	11	0.423	5	0.192
4	71	M	6	0.231	7	0.269
5	78	F	11	0.423	15	0.577
6	78	M	8	0.308	6	0.231
7	79	M	10	0.385	5	0.192
8	82	M	9	0.346	16	0.615
9	88	M	8	0.308	10	0.385
10	88	M	5	0.192	16	0.615
11	89	M	11	0.423	5	0.192
12	89	M	8	0.308	3	0.115
13	90	M	4	0.154	6	0.231
14	91	M	13	0.5	13	0.5
15	92	M	7	0.269	15	0.577
16	92	M	7	0.269	4	0.154
17	94	M	8	0.308	10	0.385
18	95	M	8	0.308	15	0.577
19	98	M	8	0.308	10	0.385
20	99	M	7	0.269	10	0.385
21	100	M	5	0.192	7	0.269
22	102	M	6	0.231	0	0
23	109	M	20	0.769	8	0.308
24	111	F	10	0.385	7	0.269
25	115	F	11	0.423	11	0.423
26	121	M	6	0.231	4	0.154
27	127	M	17	0.654	11	0.423

Table 6: Out-degree and in-degree centrality values for Cohort 2, PS I.

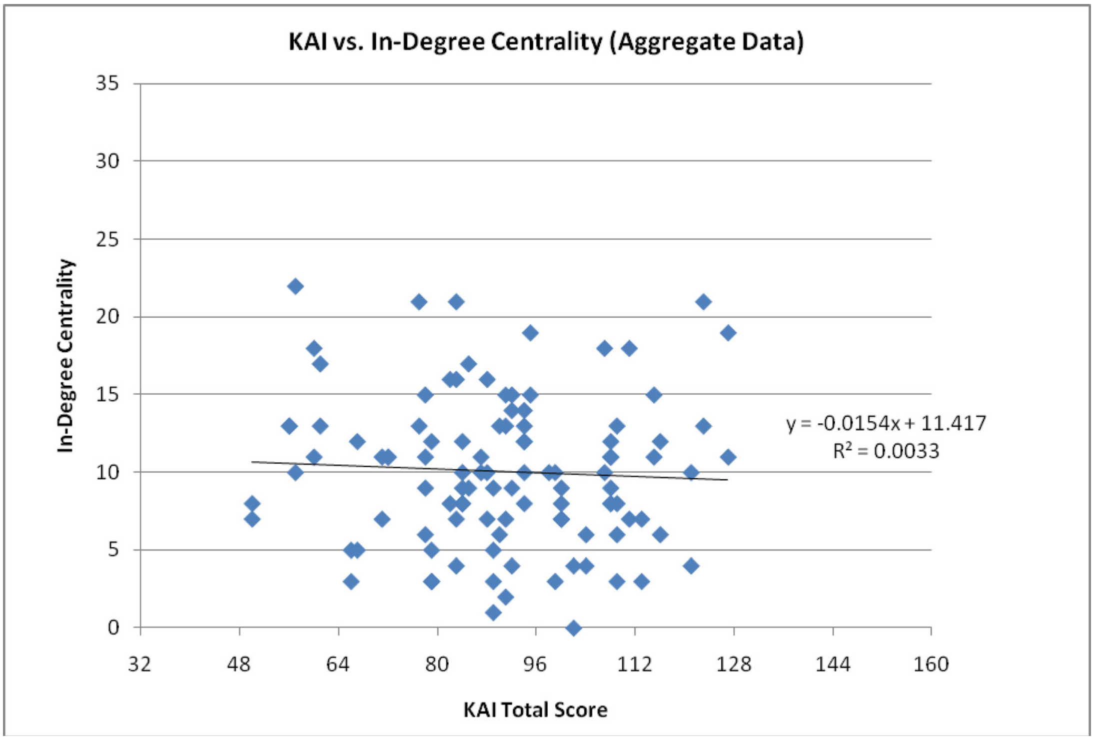

Figure 5: Regression analysis of in-degree centrality vs. KAI score (both cohorts and courses).

Future work in this area will need to employ content analysis to explore the relationships between A-I cognitive style and the types of communication students utilize (e.g., explanatory, challenging, etc.) to see if any additional links can be found.

Clique Analysis: Sub-Group Formation and Composition

To explore the impact of cognitive style on the formation and structure of on-line sub-groups, UCINET was used to perform a clique analysis on both cohorts. In social network theory, a *clique* is a group of 2 or more (in most analyses, 3 or more) individuals, all connected to each other by strong ties (i.e., reciprocal relationships) within a directed network [10,24]. Since cliques represent maximally complete sub-graphs, it is one of the more stringent methods for identifying sub-groups. Other methods (e.g., N-cliques, N-clans, K-plexes, etc.) relax the definition of the sub-group by allowing more indirect connections among its members.

For our sample, there were no cliques in either cohort with more than three members. The number of 2-member cliques was prohibitively large for presentation here, so we will focus on the 3-member cliques. Tables 7 and 8 show the composition of the 3-member cliques within each cohort

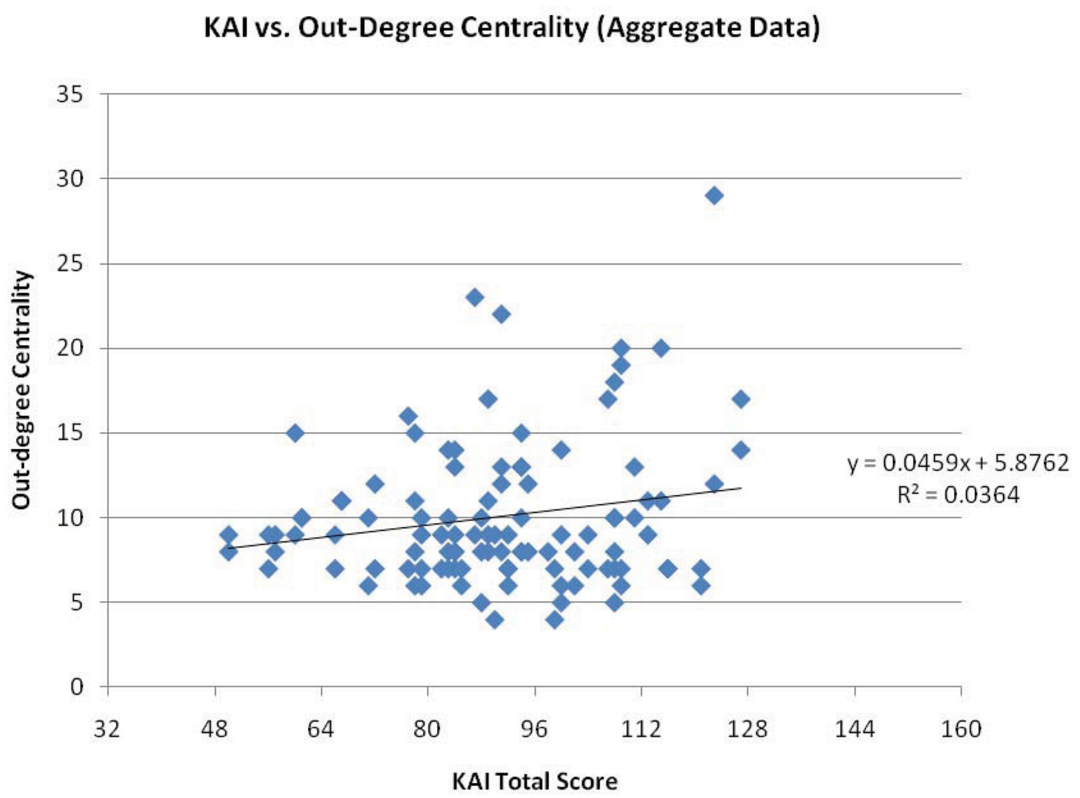

Figure 6: Regression analysis of out-degree centrality vs. KAI score (both cohorts and courses).

and class, indicating the clique members by student number and corresponding KAI total score. This level of detail is provided to help distinguish between different students within a cohort who had the same KAI score.

A number of interesting findings were revealed in this analysis. First, the number of cliques increased substantially in both cohorts from the first course to the second. This can easily be seen in Tables 7 and 8, where (for example) only one clique formed in Cohort 1 in PS I, while 20 cliques formed for this cohort in PS II. This increased participation is summarized in Table 9, where the percentage of students participating in cliques has been computed for each cohort in general and for the male and female students within each cohort, respectively. No consistent patterns in terms of clique membership emerged relative to gender. In general, the marked increase in the number of cliques and in student participation can be combined with the observed increases in overall

Class	Clique #	Clique Members (*KAI Score*)			KAI Range
PS I	1	11 (*84*)	12 (*84*)	14 (*87*)	3
PS II	1	7 (*79*)	20 (*107*)	28 (*123*)	44
	2	13 (*85*)	20 (*107*)	28 (*123*)	38
	3	20 (*107*)	21 (*108*)	28(*123*)	16
	4	6 (*77*)	11 (*84*)	28 (*123*)	46
	5	11 (*84*)	21 (*108*)	28 (*123*)	39
	6	12 (*84*)	14 (*87*)	28 (*123*)	39
	7	12 (*84*)	21 (*108*)	28 (*123*)	39
	8	14 (*87*)	17(*94*)	28 (*123*)	36
	9	6 (*77*)	13 (*85*)	28 (*123*)	46
	10	2 (*60*)	7 (*79*)	20 (*107*)	47
	11	2 (*60*)	9 (*83*)	20 (*107*)	47
	12	3 (*61*)	5 (*72*)	8 (*83*)	22
	13	3 (*61*)	5 (*72*)	26 (*115*)	54
	14	6 (*77*)	8 (*83*)	16 (*94*)	17
	15	9 (*83*)	20 (*107*)	21 (*108*)	25
	16	10 (*84*)	15 (*91*)	19 (*104*)	20
	17	1 (*57*)	10 (*84*)	19 (*104*)	47
	18	15 (*91*)	18 (*100*)	19 (*104*)	13
	19	14 (*87*)	17 (*94*)	26 (*115*)	28
	20	1 (*57*)	7 (*79*)	20 (*107*)	50

Table 7: Cliques with three members—Cohort 1.

network density to confirm a trend toward greater cohesiveness and student engagement within this particular cohort-based learning environment over time.

In terms of cognitive style, several interesting findings emerged from the clique analysis as well. First, the fact that the vast majority of the cliques formed were highly heterogeneous with respect to cognitive style was intriguing. Recall that homogeneous style sub-groups are defined as those whose individual KAI scores fall within a range of 10 points. In general, homogeneous groups experience less tension and controversy due to the inherent similarities in problem solving approach [18]. Research has shown that in face-to-face interactions, style gaps of 20 points or more are noticed almost immediately and can even lead to serious conflict in the earliest stages of problem solving [3,9,18]. Hence, we might expect that students engaged in e-Learning

Class	Clique #	Clique Members (*KAI Score*)			KAI Range
PS I	1	4 (*71*)	14 (*91*)	27 (*127*)	56
	2	2 (*56*)	12 (*89*)	25 (*115*)	59
	3	3 (*67*)	5 (*78*)	15 (*92*)	25
	4	8 (*82*)	14 (*91*)	24 (*111*)	29
	5	1 (*50*)	8 (*82*)	14 (*91*)	41
PS II	1	5 (*78*)	12 (*90*)	13 (*91*)	13
	2	6 (*78*)	12 (*90*)	13 (*91*)	13
	3	12 (*90*)	13 (*91*)	14 (*92*)	2
	4	9 (*88*)	13 (*91*)	24 (*127*)	39
	5	2 (*56*)	11 (*89*)	13 (*91*)	35
	6	2 (*56*)	13 (*91*)	24 (*127*)	71
	7	13 (*91*)	14 (*92*)	21 (*109*)	18
	8	13 (*91*)	21 (*109*)	24 (*127*)	36
	9	3 (*67*)	4 (*71*)	17 (*95*)	28
	10	3 (*67*)	17 (*95*)	22 (*111*)	44
	11	3 (*67*)	16 (*94*)	22 (*111*)	44
	12	12 (*90*)	14 (*92*)	17 (*95*)	5
	13	5 (*78*)	12 (*90*)	17 (*95*)	17
	14	20 (*102*)	21 (*109*)	24 (*127*)	5
	15	21 (*109*)	22 (*111*)	24 (*127*)	18
	16	9 (*88*)	22 (*111*)	24 (*127*)	39

Table 8: Cliques with three members—Cohort 2.

Cohort	Class	% All Students in Cliques	% Male Students in Cliques	% Female Students in Cliques
1	PS I	3/27 = 11.1 %	3/17 = 17.7%	0/10 = 0%
	PS II	22/28 = 78.6%	14/17 = 82.4%	8/11 = 72.7%
2	PS I	12/27 = 44.4%	8/23 = 34.8%	4/4 = 100%
	PS II	16/24 = 66.7%	13/21 = 61.9%	3/3 = 100%

Table 9: Clique participation summary data across cohorts and courses.

would also tend to seek out classmates with similar styles when given the choice—as they were given in these discussion forums. Yet only 4 of the 42 cliques (9.5%) formed across both cohorts and courses were homogeneous in style; the remaining 38 cliques (90.5%) were highly heterogeneous, with a mean KAI range of 35.2 points. Although the content of the discussion forums will need to be examined further to discern the nature of the students' interactions within the cliques (i.e., were they "friendly" or "hostile"), this finding suggests that the on-line environment may serve to mask cognitive differences in ways that enable more diverse networks to form more readily.

We also found that the mean KAI scores for students who belonged to more cliques (⩾4) tended to be more innovative. In particular, in Cohort 1, students 28 (KAI=123), 21 (KAI=108), and 20 (KAI=107) belonged to 9, 7, and 4 cliques, respectively (with all other students in the cohort participating in fewer than 4 cliques); their resulting mean KAI score is 112.7. Likewise, in Cohort 2, students 24 (KAI=127), 22 (KAI=111), 21 (KAI=109), 17 (KAI=95), 13 (KAI=91), and 12 (KAI=90) belonged to 8, 6, 5, 4, 4, and 4 cliques, respectively, with a resulting KAI mean of 103.8. This result, taken together with the possibility of a link between Innovation and increased out-degree centrality may indicate a connection between active engagement within an on-line environment and A-I cognitive style that will require further investigation.

Power and Leadership within the Cohorts

From the SNA literature [10,24], individuals who rank highly with respect to both in-degree and out-degree centrality within a social network are believed to have the greatest influence and/or power within that network. This influence is derived from the fact that they can successfully form many network ties and are thus seen as more powerful sources of information for the group. Additionally, they are often viewed as having a more prestigious position within a network, because many individuals seek to interact with them. Leadership within a social network is often associated with an individual's power and influence, as well as their active membership in many sub-groups, while from a problem solving perspective, leaders can come from anywhere along the A-I style spectrum, depending on who is best suited to take the lead in solving the current problem at the current time [12,18].

In this study, the students who emerged as the most influential were designated as those in the top 30-33% of the class with respect to the highest summed degree centrality metrics. Using this criterion, the most influential students from each cohort/class are listed in Table 10. As a means of identifying individuals who assumed leadership roles, students who were also members of 3 or more cliques are indicated in Table 10 as well, where the number of cliques is designated by the number of asterisks.

As expected from Adaption-Innovation (A-I) theory, the most influential students were highly heterogeneous with respect to cognitive style, and the emerging student leaders (as defined above) in both cohorts had diverse cognitive styles from across the A-I continuum as well. Interestingly, the most influential students differed as the cohorts progressed from PS I to PS II. That is, simply

Cohort 1 / PS I	
Student (KAI)	Summed Centrality
27 (123)	25
3 (61)	23
11 (84)	23
21 (108)	22
17 (94)	21
2 (60)	20
6 (77)	20
16 (94)	20

Cohort 2 / PS I	
Student (KAI)	Summed Centrality
23 (109)	28
27 (127)	28
5 (78)	26
***14 (91)	26
8 (82)	25
18 (95)	23
15 (92)	22
25 (115)	22

Cohort 1 / PS II	
Student (KAI)	Summed Centrality
*********28 (123)	50
***6 (77)	37
*******20 (107)	35
26 (115)	35
***14 (87)	34
2 (60)	33
1 (57)	31
9 (83)	31

Cohort 2 / PS II	
Student (KAI)	Summed Centrality
********13 (91)	37
******24 (127)	33
****21 (109)	32
****17 (95)	31
****22 (111)	31
5 (78)	26
***3 (67)	23
***14 (92)	23

Table 10: Most influential students in both cohorts (1* = 1 clique).

because a student emerged as an influential member in one course, they did not necessarily retain that position of power as their level of engagement varied in the next course. Such shifts in power and influence in an on-line classroom setting may be due to external pressures (e.g., increased time constraints) or differences in internal motivators (e.g., interest in the discussion topics).

Visualizing Social Network Structure and Interactions

Network graphs were produced for each cohort/class using UCINET's NetDraw and a multi-dimensional scaling (MDS) algorithm to help visualize the structure and dynamics of each student social network. The MDS algorithm plots nodes in relation to graph theoretic measures of their "closeness" [10, 24], which reflects the similarities in a student's choice of individuals with whom to communicate. Therefore, two students are similar to the extent that they have similar shortest paths (geodesic distances) to all other students. Thus, nodes placed close to each other in an MDS diagram represent students with similar patterns of communication and interaction within the network. Sample MDS diagrams are shown below for Cohort 1 for PS I (Figure 7) and PS II (Figure 8), respectively.

Both MDS diagrams are color coded to illustrate the out-degree metrics for each student, which can clearly be seen to increase from PS I to PS II. In addition, this visualization helps illustrate the interconnected web pattern of communication achieved in this on-line context (as opposed to a star pattern), as well as the increased network density observed within the cohort from the first course to the second. Perhaps most intriguing, however, is the proximity of the various nodes within the network in conjunction with the respective cognitive styles of the individuals they represent (shown in parentheses). Specifically, as highlighted by the orange ovals on each diagram, we see that individuals of noticeably different cognitive styles exhibited similar patterns of communication and interaction within this on-line

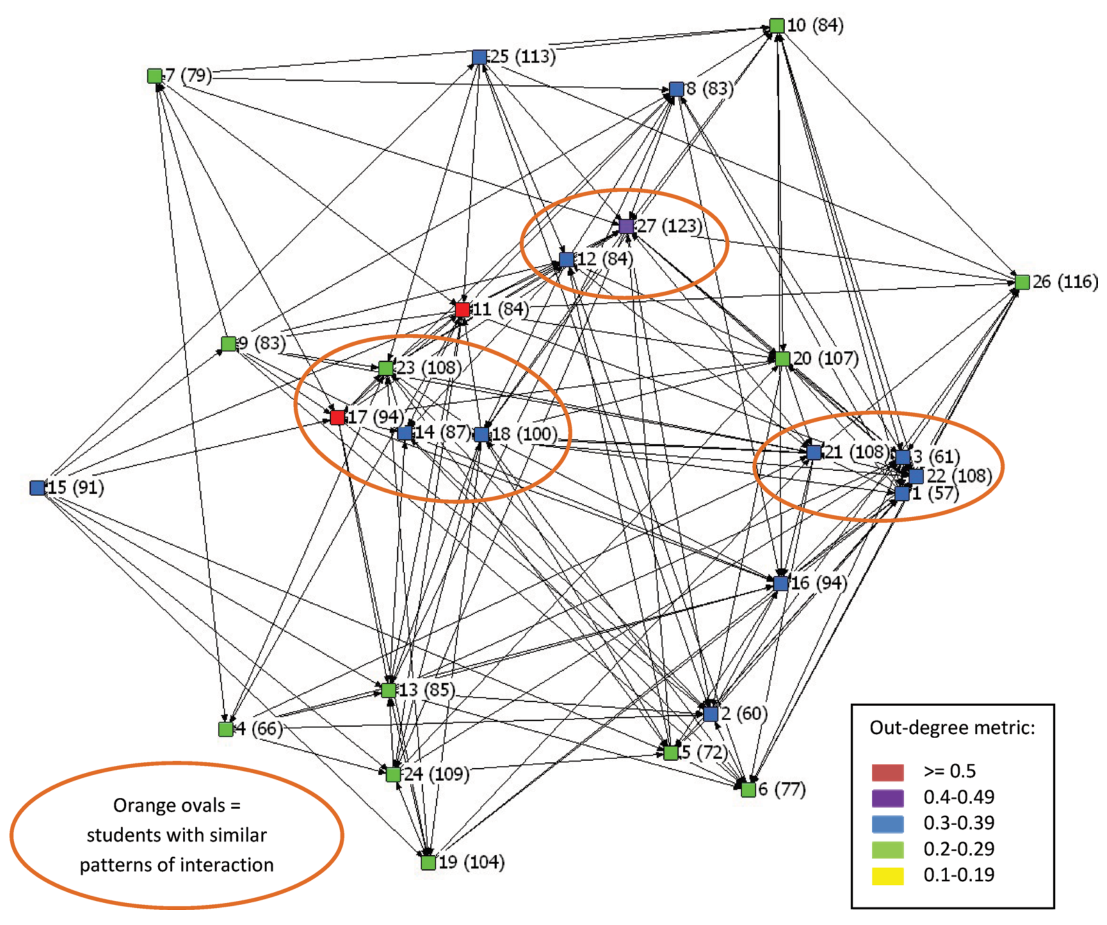

Figure 7: Multi-dimensional scaling (MDS) diagram for Cohort 1, PS I.

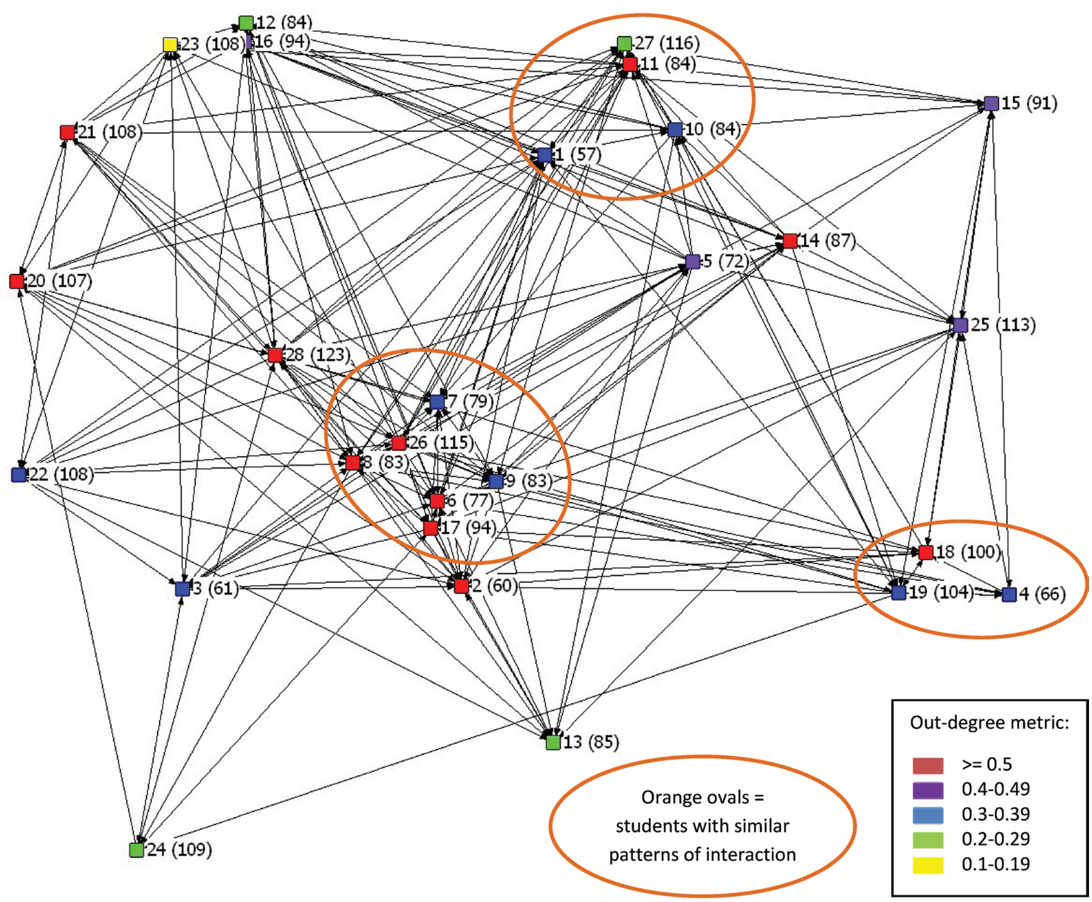

Figure 8: Multi-dimensional scaling (MDS) diagram for Cohort 1, PS II.

environment—an observation that supports the notion suggested above (in connection with the clique analysis) that cognitive differences may be less obvious (or masked) in an e-Learning context.

FINAL DISCUSSION AND FUTURE WORK

Key Results and Implications

In this study, we explored the impact of cognitive style on the structure and operation of students' social networks in an e-Learning environment. Cognitive style was measured using KAI, while social network interaction data were collected from a series of structured discussion forums within two graduate-level on-line courses. In general, a wide range of cognitive style diversity was found within the sample, with a slight adaptive skew in the overall distribution as compared with the general population and with samples from the same courses taught face-to-face. Most of this variation was exhibited in the E sub-score, which may be a reflection of the students' alignment with their job functions (which tended, on average, to be somewhat more regimented) and/or a result of their self-selection into an on-line degree program that is quite structured in its format and operations.

One of the most interesting results of this study was the highly heterogeneous nature (in terms of cognitive style) of the cliques formed by the students, combined with the similarities in communication patterns as identified by the MDS algorithm. With a mean range of KAI scores of 35 points over 90% of the cliques and the diversity of students with similar interaction patterns, it is clear that the students did not "flock together" with those of similar style throughout the series of on-line discussion forums. These findings raise some intriguing questions about the potential for on-line environments to "hide" (or at least dilute) some cognitive differences—and why this might happen. Several possible explanations for such an effect could be considered. For example, students may be more likely to gravitate towards classmates who work in similar settings and/or who have had similar experiences, whether at work or through some aspect of their personal lives. Such similarities in manifest experience (a form of cognitive level) may provide a strong enough sense of "sameness" and familiarity that differences in cognitive style (preferred approach) become less noticeable and troublesome, even though they are clearly there!

The time constraints of the discussion forums may also have contributed to the high degree of clique heterogeneity, in the sense that students were forced to respond to whomever had already made postings (or run the risk of not completing the assignment), even if that person's posting did not appeal to them. Additionally, the nature of the forum assignments may have contributed to a masking of cognitive differences. Although the forums provided students with a venue to discuss their preferences for managing structure, as well as their personal experiences with individuals of diverse cognitive styles across many aspects of the problem solving process, the students were not explicitly told to "work as a team" to produce a single shared deliverable. Instead, the forums focused on social networking as a product (i.e., debate, information exchange, and knowledge construction as the outcome), for which the students received individual grades. Such tasks may not be perceived in the same way as the shared creation of a concrete artifact for which the team is assigned a common grade. What remains to be seen, then, is whether cognitive style had an impact on the *nature* of all these interactions—i.e., were the heterogeneous cliques functioning in a constructive manner, or did their cognitive style differences create interpersonal tension (e.g., through confrontation) within their discussions? In addition, with only small cliques formed in these cohorts, we are left to wonder whether larger cliques would exhibit the same style diversity as that observed here.

Finally, in terms of influence and leadership within the students' social networks, our findings support the view that problem solving leaders can and do emerge from anywhere along the cognitive style spectrum [12][18], with both the more adaptive and the more innovative individuals exerting influence within the network. The nature of this influence may be quite different, however, as the emerging "leader" strives to manage both the immediate problems faced by their group (in this case, the tasks assigned in the discussion forums) and the diversity of the group itself. Kirton refers to a group's original shared task as Problem A, while managing the members' individual cognitive differences is Problem B [18]. Clearly, the effective leader needs to understand and be able to manage both wisely and well, whether he or she is operating face-to-face with a team or in an on-line environment.

Future Work

The impact of individual psychological differences on the participation and patterns of communication in social networks is a relatively new domain of research. This exploratory study revealed several interesting links between cognitive style and the interaction patterns of students in on-line social networks that will serve as the foundation for future work. Since cognitive style is known to influence an individual's preferred manner of problem solving in face-to-face settings, an in-depth content-based analysis of discussion forum transcripts will be instrumental for elucidating whether cognitive style impacts the types of communication students utilize when interacting with their peers on-line. Content-based analysis will also help provide insight into how cognitive style may influence the social dynamics within cliques and whether the on-line format masks differences in cognitive style.

Future research questions will include whether members of heterogeneous cliques tend to challenge and debate one another with greater frequency than members of cliques that are homogeneous with respect to cognitive style. Additional data from future cohorts will also be helpful for discerning whether a statistically significant relationship exists to support our preliminary observations that individuals with more innovative cognitive styles exhibit a greater propensity for expansiveness within social networks and/or a greater proclivity for belonging to more cliques. These and other research topics represent the beginning of what promises to be a rich field for further investigation.

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