Relating Social Network Structure to Uncertainty and Social Interaction in an Engineering Design Challenge

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Introduction

The open-ended nature of engineering design problems implies uncertainty; there is no one, correct solution and no best path to take to achieve a viable solution (Sullivan, 2008). Moreover, engineers must learn to communicate effectively in diverse, cross-disciplinary teams (Roy, 2009), and communication is a primary tool for navigating uncertainty (Babrow, 2001). From a communication perspective, sources of uncertainty can be clustered into identity, relational, and instrumental meanings (Jordan & Babrow, 2013). Jordan and McDaniel (2014) defined uncertainty as a "subjective experience of doubting, being unsure, or wondering" (p. 492), and described how young learners experienced and responded to uncertainty from various sources in a collaborative engineering design project. These authors found peer social support to be critical for individuals working in homogenous groups (wrt: experience, and goals) to manage uncertainty and to forward design work.

However, working on engineering design problems in heterogeneous groups may increase the diversity of uncertainty sources and responses, provide different opportunities for expressing uncertainty, and more strategies for managing uncertainty. Therefore, the present study featured a diverse cohort of engineering design participants, working in small collaborative sub-groups, structured for heterogeneity. Each type of participant brought a different set of skills, background, and experience to a summer engineering research experience; the combined value of their diverse "tools" was theorized to enrich both the learning process and the potential outcomes of a modeling design activity (Page, 2007).

These understandings of using social interaction to manage uncertainty, coupled with scholarship on social networks for learning (Wasserman, & Faust, 1994; Yoon, 2011) led to the following research questions:

RQ1: What is the structure of the social network with respect to who is recognized as influential to learning?

RQ2: What uncertainty did participants report, how was uncertainty managed, and how did these sources of and responses to uncertainty relate to the structure of the network?

RQ3: How did the social network influence the outcome of the collaborative, engineering design task?

Method

The diverse cohort of 27 participants (13 female; 14 white) included 15 undergraduates from across the U.S., seven local teachers, two local high school students, and three international students. This analysis focuses on the first two weeks of the eight-week summer engineering research program when participants were assigned to nine heterogeneous three-member groups to accomplish two tasks: fabricate a solar cell and model the lab processes digitally using PC1D (PVEducation, 2017) software. The modeling objective was to maximize the solar cell efficiency by modifying parameters such as pyramid height. Although participants received an initial lecture on the modeling software and activity, the activity itself was an ill-structured design challenge. Groups were able to collaborate with other groups and access mentors for guidance.

Primary data sources included daily reflection responses (open-ended; Likert) regarding participants' uncertainty and management of uncertainty, audio-video recordings and field notes of program activities, and each group's presented maximum cell efficiency. Additionally, participants completed a post-survey at the conclusion of the two-week challenge; for this, each participant rated all cohort members (5-pt Likert) as to how influential each participant was to their learning.

Following Jordan and McDaniel's (2014) framework, two researchers independently coded and reconciled open-ended survey responses regarding uncertainty about (a) fundamental scientific content, (b) engineering identity, (c) the PC1D software operability, and (d) relationships with other program participants. The frequencies of each uncertainty source and management technique reported by each participant as well as participants' demographics, position (e.g. REU), project grouping, and dorm residency, in addition to the efficiency of each group's optimal simulated solar cell modeled in PC1D were culled into an attribute list. Finally, a social network analysis (Scott, 2017) was conducted using R from a weighted adjacency matrix developed from the post-survey sociogram items. Bivariate correlations using Pearson's r between cluster formation, sources of uncertainty, and management of uncertainty were conducted in SPSS.

Results and discussion

The network formation was not random. Four participant clusters emerged (RQ1), one of which contained all of the teachers as well as the other two members of one teacher's group. A correlation analysis indicated that group assignment most related to cluster formation (r=.833, p<.001), followed by dorm lodging (r=-.502, p=.009), which differentiated another two clusters. The fourth cluster contained the two groups without a teacher. This clustering reflects tendency towards homophily.

Participants reported managing relationship uncertainty with avoidance (RQ2; r=.343, p=.087), and managing knowledge uncertainty by seeking out peers (r=-.373, p=.060) or relying on oneself (r=-.337, p=.092). Although with this small sample we don't quite see significance, this may explain why the teacher clustering; perhaps they recognized other teachers as their peers, sought to manage knowledge uncertainty, and avoided their other groupmates due to relationship uncertainty. Uncertainty about knowledge (r=-.350, p=.080) and relationships (r=-.367, p=.065) correlated with the formation of the dorm-dwelling cluster formation, shy of significance. Perhaps within this cluster, participants felt comfortable acknowledging their uncertainty.

The three clusters containing the seven teacher-member groups all produced similar cell efficiency results in their modeling task (RQ3). One group in the fourth cluster, which lacked teachers, took a different approach to the design task: they eliminated any factor, even the unavoidable, that reduced cell efficiency. This approach yielded more than twice the cell efficiency of the other groups and was lauded by the expert engineers as the best approach to the problem, but was not disseminated through the network with the other clusters.

According to a pagerank analysis, the five most influential participants include the four most advanced engineering students and a novice community college student who was highly interactive. Observations and field notes indicate that this novice student frequently sought and shared knowledge, acting as an arbiter for the highly knowledgeable international graduate student in his group. This seems to suggest that participants primarily valued knowledge, but a participant acting as a "social glue" may be equally valuable.

Significance

The results suggest that identities (e.g. teacher) and relationships (e.g. dorm-mates) developed outside of the learning arena are a bigger indicator of learning influence that formally imposed group structures, and therefore may offer unique opportunities to help novice engineers manage uncertainty through social interaction. By purposefully dispersing known identities (e.g. teachers) across formal groups, cross-group communication channels appear to form, allowing knowledge and ideas to disseminate more broadly. On the other hand, social clusters lacking connections to such broadly disseminated identities may develop alternative solutions in isolation. These preliminary findings may have implications for designing project groups for engineering design projects and other ill-structured tasks. Finally, socially recognized influence on learning typically highlights the most knowledgeabl /experienced participants as primary; however, high levels of interactivity and bi-directional engagement of the social network by a participant may be valued as equally influential to others' learning.

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