Using Social Interaction Trace Data and Context to Predict Collaboration Quality and Creative Fluency in Collaborative Design Learning Environments

Ninger Zhou[1]
Lorraine Kisselburgh[2]
Senthil Chandrasegaran[3]
S. Karthik Badam[4]
Niklas Elmqvist[4]
Karthik Ramani[5]

Author Note
[1]School of Education, University of California, Irvine
[2]Lorraine Kisselburgh, Burton Morgan Center for Entrepreneurship, Purdue University
[3]Senthil Chandrasegaran, Department of Computer Science, University of California, Davis
[4]S. Karthik Badam, Department of Computer Science, University of Maryland
[4]Niklas Elmqvist, Department of Computer Science, University of Maryland
[5]Karthik Ramani, School of Mechanical Engineering, Purdue University

Correspondence concerning this article should be addressed to Ninger Zhou, School of Education, University of California, Irvine. Email: znenancy@gmail.com

Abstract

Engineering design typically occurs as a collaborative process situated in specific context such as computer-supported environments, however there is limited research examining the dynamics of design collaboration in specific contexts. In this study, drawing from situative learning theory, we developed two analytic lenses to broaden theoretical insights into collaborative design practices in computer-supported environments: (a) the role of spatial and material context, and (b) the role of social interactions. We randomly assigned participants to four conditions varying the material context (paper vs. tablet sketching tools) and spatial environment (private room vs commons area) as they worked collaboratively to generate ideas for a toy design task. We used wearable sociometric badges to automatically and unobtrusively collect social interaction data. Using partial least squares regression, we generated two predictive models for collaboration quality and creative fluency. We found that context matters materially to perceptions of collaboration, where those using collaboration-support tools perceived higher quality collaboration. But context matters spatially to creativity, and those situated in private spaces are more fluent in generating ideas than those in commons areas. We also found that interaction dynamics differ: synchronous interaction is important to quality collaboration, but reciprocal interaction is important to creative fluency. These findings provide important insights into the processual factors in collaborative design in computer-supported environments, and the predictive role of context and conversation dynamics. We discuss the theoretical contributions to computer-supported collaborative design, the methodological contributions of wearable sensor tools, and the practical contributions to structuring computer-supported environments for engineering design practice.

Keywords: computer-supported collaborative design, situative learning theory, conversation dynamics, material context, spatial context, wearable sensors.

Using Real-time Trace Data to Predict Collaboration Quality and Creative Fluency in Collaborative Engineering Design Environments

One of the ultimate goals of engineering education is to prepare engineers to think and function effectively as part of a team, while achieving high levels of collaboration and creative fluency in collaborative design settings (ABET, 2014; Détienne, Baker, Vanhille, & Mougenot, 2017; Dym, Agogino, Eris, Frey, & Leifer, 2005). High quality collaboration, defined as effective interaction in groups that foster interdependent action and equitable status (Lewis, 2006), and creative fluency, defined as the ability to generate a large number of novel ideas (Dumas, Schmidt, & Alexander, 2016; Guilford, 1967), are important goals for engineering learning but also crucial to the efficiency of design cycles in engineering practice (Charyton & Merrill, 2009). Despite its importance, learning to design both creatively and collaboratively has been particularly challenging due to the multimodal nature of collaborative engineering design, where engineers interact both verbally, as well as through visual and material cues embodied in design practices (Reid & Reed, 2005). These challenges stemming from the multimodality nature of collaborative design have been further complicated by recent advancements in computer-supported design tools (Cheng, Li, Sun, & Huang, 2016; Shen, Hao, & Li, 2008). Therefore, to promote positive outcomes in collaborative engineering design, it is imperative to understand social interaction behaviors in the design process as they are situated in particular spatial and material contexts. However, understanding interaction dynamics in computer-supported design environments has heretofore been undermined by a lack of effective methodological tools (Brisco, Whitfield, & Grierson, 2018; Fischer et al., 2016; Stahl, Koschmann, & Suthers, 2006; Vuletic et al., 2018).

In addition, the situative nature of collaborative engineering design adds to the complexity of studying interaction dynamics. Research has demonstrated that collaborative design practices are highly influenced by the environments in which they are embedded, including the spatial context within which they interact (e.g., rooms, furniture, walls, traffic patterns, noise, and lighting) as well as the material artifacts (i.e. design tools and medium) used during the design process (Fayard, 2012; Gaver, 1996). Studies have indicated that specific characteristics of the physical environment can enhance creative performance (Dul & Ceylan, 2011; 2014), and that material artifacts play an important role in idea representation and collaboration (Johri & Olds, 2011). However, research has not fully addressed the impact of recent advancements in technologically-enhanced design tools such as interactive mobile tablet devices, which provide new material contexts and affordances for brainstorming, sharing, and visually representing ideas during collaborative design (Fischer et al., 2016; Martinez-Maldonado et al., 2017; Palou et al., 2012). Although the mobile tablet platform, characterized by portability, accessibility, and connectivity, is useful for the joint construction of new ideas (Looi et al., 2013), sketching collaboratively on tablets imposes new challenges to engineering design and the study of interaction processes during learning. Considering that researchers have identified strong associations between interaction patterns and collaborative engineering design outcomes (Bucciarelli, 1994; Terenzini et al., 2001), there is a critical need to examine the relationships between social interaction processes and collaborative design outcomes in different spatial and material contexts.

In light of the challenges to studying interaction dynamics in multimodal and context-rich engineering design settings, and the need to better understand the dynamic processes of collaborative design in computer-supported environments, researchers have looked to recent developments in wearable and sensor technologies. One of the promising tools that can generate real-time trace data on various social interaction dynamics are wearable sociometric sensors, which have been used to study the relationship between interaction dynamics and group intelligence, as well as performance in organizational and academic settings (Woolley, Chabris, Pentland, Hashmi, & Malone, 2010). In this study, we adopt wearable sensor technologies to unobtrusively collect social interaction data and identify key factors that are predictive of two indicators of successful collaboration design outcomes: Collaboration Quality and Creative Fluency. In doing so, we contribute to the field of situative cognition and human behavior with computers by introducing a new method for data collection and analysis in collaborative design groups, and we extend theoretical understanding of the underlying relationship between social interaction dynamics and collaborative engineering design outcomes. Furthermore, our findings will have practical implications in revealing the interaction dynamics that are conducive to high quality creative collaborative design performance in computer-supported environments.

Theoretical Background

Collaboration Quality and Creative Fluency in Engineering Design

Creativity has become a critical factor in engineering design, and the need to nurture creativity in engineers has become more evident as both industry and academic settings are in great demand of innovation throughout the engineering design process (Détienne et al., 2017; Dumas et al., 2016; Howard, Culley, & Dekoninck, 2008).We define creativity in design groups as the generation of novel ideas by two or more interdependent members who can influence each other during group interaction (Amabile, 1996; Paulus, 2000). Classically, there are four key signatures of creativity: fluency, flexibility, originality, and elaboration of ideas generated by individuals involved in an activity. Fluency is the ability to generate a large number of ideas, flexibility is the ability to generate a wide variety of ideas, originality is the production of novel ideas, and elaboration is the process of building upon ideas proposed by others (Guilford, 1967; Shah, Smith, & Vargas-Hernandez, 2003). Specific to the field of engineering, creativity is viewed as the creation of novel and useful products, processes, or new artifacts and ideas (Thompson & Lordan, 1999).

In this study, we focus on the fluency dimension of creativity and engage students in a group task where they brainstorm toy design ideas in a process that encourages the generation of as many ideas as possible without reflecting on originality and flexibility. Previous studies on creativity in engineering education have used similar methods to examine creative fluency by enumerating the quantity of new sketches produced by students in design tasks (Charyton & Merrill, 2009). In most cases, creativity is studied as the production of solutions or artifacts while working independently (Charyton & Merrill, 2009). The current study differs from previous research in that we situate creative fluency in collaborative contexts in order to gain insight into influential factors for collaborative creative fluency.

Situative Theories of Collaborative Design Learning

Johri & Olds (2011) discuss the central construct of *situativity*, or learning as a situated activity, and its importance for learning in engineering design. The situative perspective views knowledge as socially constructed and constituted within a specific context (Clancey, 2009), with learning occurring through active participation in a community of practice (Lave, 1991; Lave & Wenger, 1991). Specifically, learning is theorized to arise through dynamic construction of creative work, within a specific context, and through active engagement and participation in meaningful practices (Sawyer & Greeno, 2009).

The situative perspective draws from theories of situated cognition (Brown, Collins, & Duguid, 1989; Greeno, 1989), situated action (Norman, 1993; Suchman 1987, 2007), and situated interaction (Dourish, 2001). However, situative theories of learning differ from the behaviorist and cognitive approaches by viewing knowledge as “distributed among people and their environments, including objects, artifacts, tools, books, and the communities of which they are a part” (Greeno, Collins & Resnick, 1996, p. 17). Within this perspective, learning is theorized to be constituted through sociomaterial practices that are constrained and enabled by the affordances of the material and spatial environments (situated learning theory; Sørensen, 2009).

To broaden theoretical insights into engineering and design learning, Johri & Olds (2011) introduced analytic lenses, including (a) the social and material context, (b) the role of activities and interactions. In the following sections, we draw from these analytic lenses to frame our study and review the literature salient to collaborative design learning in computer-supported environments.

The material and spatial context for engineering design. Engineering design learning is situative and embedded within the material and spatial environment (Johri & Olds, 2011; de Vries & Masclet, 2013). In the material context of engineering design, the influence of material tools on human cognition is particularly salient, and design learning often requires students to develop a hybrid posture through their bodies’ interactions with a variety of material tools (Sørensen, 2009). For example, the emergence of mobile touch-based devices has enriched the materiality of engineering design learning by introducing touch-based sketch and design applications to improve the affordances provided by traditional pen and paper platforms (Shen et al., 2008). However, while engaging in collaborative design on the mobile touch-based platforms, design students are expected to interact with and interpret digital material representations (e.g., design sketches), as well as the digital cues generated by other team members (Sørensen, 2009). In the case of our current study, using the digital sketches created on the tablets as a point of departure, the engineering students engaged in social interactions to construct meaning and design ideas collaboratively. Such dependence of the social interaction dynamics on digital materials and cues in engineering design settings invites investigation into the affordances and interaction patterns that are supported by digital platforms. Therefore, we examine the role of the socio-material context in the collaborative design performance of engineering design teams.

In addition, collaborative engineering design is situated within a variety of spatial contexts (e.g., formal and informal learning spaces, structured or flexible physical layouts, private or public settings, and with few or many environmental distractions), which are capable of facilitating or inhibiting certain interactions or behaviors (Jordan & Henderson, 1995). Previous research has shown that in collaborative settings each students' interpretation of the spatial context (e.g., the perception of the space, the quality of lighting, the actions that are afforded) influences their behaviors, social interactions, learning, as well as collaborative outcomes (Baron, 2006; Leander, Phillips & Taylor, 2010). For example, the physical arrangements in learning spaces have been found to mediate students' level of participation in social interactions (Roth, McGinn, Woszczyna, & Boutonne, 1999), and office layouts influence organizational culture and job satisfaction (Zerella, von Treuer, & Albrecht, 2017). However, research on the role of spatial contexts in collaborative engineering design has been limited. In this study, we explore whether spatial context is an important predictor of collaborative design performance.

Social interaction in collaborative engineering design. In the past decade, educators and researchers have strived to help engineering students gain social interaction skills in collaborative learning environments, which are transferrable to industry climates that rely on effective social interaction to produce desirable design outcomes (Bucciarelli, 1994; Pahl, Beitz, Feldhusen, & Grote, 2007). Social interaction has a critical role in collaborative design learning because engineering students can provide scaffolding for each other to build design knowledge and enhance the quality of design outcomes. For example, research has found that students perform significantly better in engineering design and problem solving when they learn through collaborative tasks than through traditional lecture/discussion formats (Terenzini et al., 2001). Therefore, it is important to engage engineering students in collaborative design settings and help them develop social interaction patterns that are conducive to collaborative outcomes.

In efforts to engage students in collaborative design, advances in collaborative technologies, including applications, devices, and infrastructures, have created new affordances for social interaction. In comparison with the traditional medium of paper and pen for early stage design sketching, computer-based interfaces allow engineering students to dynamically represent design ideas (Stahl et al., 2006) and efficiently communicate their ideas in a tangible medium (Dillenbourg, 2005). Functions such as real-time synchronization of sketches across devices can also augment collaborative meaning construction by allowing students to access other team members' sketches as a scaffold in the construction of new ideas. For instance, sketching on tablets and sharing the screen with others can create a material space in which teams of engineers explicitly represent their design knowledge and ideas, and visualize them in a collaborative space that facilitates design processes. For example, in our earlier work, collaborative design systems enable learners to generate and share visual representations of design ideas through the use of collaborative design tablets and shared design walls (MASKED; Martinez-Maldonado et al., 2017).

In both the traditional paper-based and computer-supported collaborative environments, previous research has identified that engineer students need to attend to both the visual cues such as design sketches, as well as social interaction dynamics among collaborators, which has created challenges to design outcomes (Reid & Reed, 2007). However, there is a gap in research in understanding the parallel negotiation of verbal and visual design ideas, and specifically understanding the micro-level interaction dynamics in both paper-based and computer-supported design environments (Martinez-Maldonado et al., 2017). Understanding the dynamic processes of design practice can help to foster positive interaction dynamics that benefit group processes as well as quality outcomes in collaborative design (Olguin & Pentland, 2010; Pentland, 2012).

Sociometrics as Predictors of Collaborative Outcomes

In collaborative engineering design tasks, the dynamics of social interaction play a central role in group work (Brereton, Cannon, Mabogunge, & Leifer, 1996). In the past, researchers have used conversation analysis of groups, analyzing recorded conversation transcripts in order to identify how understanding and meaning is constructed through the talk of participants (Koschmann, 2013). Alternatively, discourse analysis has been used to analyze "both macro (conversational turns) and micro levels (statement units)" of discourse (Jeong, 2013, p. 176). However, these analytic methods are labor-intensive and often confined to small segments of text, requiring researchers to manually peruse transcripts, develop coding schemes, train coders, and assure inter-rater reliability among multiple coders. As a result, the time required for such methods has been a hindrance for researchers in analyzing interaction discourse over longer periods of time, or with larger sets of data. Furthermore, obtrusive recording of conversations puts the pressure of social desirability on participants and can influence the validity of data gathered from group conversation. Participants may avoid or increase certain interaction patterns due to social desirability (Guest, Bunce, & Johnson, 2006). Finally, researchers have acknowledged the difficulty in studying social interaction in non-traditional settings (i.e., computer-supported) or long periods of time (Looi, Wong & Song, 2013).

Recent advances in computational approaches have produced innovative methods to ameliorate the challenges in studying social interaction dynamics, including measuring brain waves, physiological indicators, and capturing data on body, postural, and speech activity (Delaherche et al., 2012). One such approach uses wearable sociometric devices to unobtrusively collect real-time data on the speech and behavioral patterns of groups (Olguin & Pentland, 2008). Using such devices, researchers can quantify dynamics of interaction in collaborative teams using sociometric data, without recording conversations or conducting verbal analysis. In recent research, sociometric data have been found to be important indicators of collaborative performance in a variety of contexts (Kim, Chang, Holland & Pentland, 2008). For example, successful teams in a business plan development task outperformed less successful teams on several sociometric measures, including speech participation and energetic body movement (Olguín-Olguín & Pentland, 2010). Additionally, researchers have demonstrated that sociometric measures can predict creativity in teams. For example, Triparthi and Burleson (2012) found that body movement and face-to-face interaction measured by sociometric badges over the course of multiple days strongly predicted creative outcomes for teams working on software coding projects. While these empirical studies demonstrate the promise of using sociometric trace data to predict creative and collaborative outcomes in teams, none have yet examined the micro-level interactional dynamics of groups engaged in collaborative engineering design learning.

In summary, the importance of spatial and material context as well as social interaction dynamics, has been demonstrated in collaborative settings. However, there is a dearth of knowledge about the relationships between the context, interaction dynamics and collaborative design outcomes in design learning. Furthermore, there is little empirical evidence regarding the dynamic relationship between interaction processes and creative collaborative outcomes, an area that could benefit from the use of wearable data collection tools. Extending research in these domains provides important contributions to theoretical development in situative learning theory, particularly in the unique context of engineering design. Therefore, the research questions we investigate in this study include:

a. What are the roles of spatial and material context and social interaction dynamics in predicting collaboration quality in engineering design teams?
b. What are the roles of spatial and material context and social interaction dynamics in predicting creative fluency in engineering design teams?

Methods

This study was conducted as part of a larger project that developed a tablet-based collaborative engineering design tool called *skWiki* (MASKED), described below. In this study, we used a 2x2 design to examine whether material contexts (*paper* vs. *skWiki*), spatial contexts (*Commons* vs. *Private room*), and social interaction dynamics can predict collaborative quality and creative fluency in design teams.

Participants

Participants were sixteen graduate students (14 men and 2 women), ranging in age from 21 to 37 years (M=25.25, SD=3.92), enrolled in a graduate level mechanical engineering design course. Because industry practices often involve engineers from a wide range of background and experience working on the same design tasks, we also engaged participants from diverse backgrounds in this study. All the participants are 1st to 3rd year graduate students in engineering majors, with an average of 2.19 years (Standard Deviation=0.83) in their program. The average rating of the participants' self-report of communication skills is 3.44 (Standard Deviation=1.26) on a 5-point Likert scale. The participants were randomly assigned to the experiment conditions.

Prior to the study, participants learned fundamental techniques of engineering design, including ideation techniques such as brainstorming, brainsketching (van der Lugt, 2002), SCAMPER, "combining things" (Michalko, 2006), and how to understand the *play value* of products (Kudrowitz & Wallace, 2010). All participants were skilled in visualizing their design ideas with prior training in sketching as a means for visual thinking (Taborda et al., 2012).

Design Context

The design teams were assigned to work on collaborative design tasks in one of four types of environments that varied spatially and materially (see Figure 1).

Figure 1. Collaborative teams during a toy design session. Clockwise from top left: 1) students use skWiki design tablets in Private room; 2) students use skWiki design tablets in Commons area; 3) students use pen and paper in Commons area; 4) students use pen and paper in Private room.

Spatial context. The design teams were assigned to work in one of the two spatial environments that simulated informal and formal contexts. Prior research has indicated that informal learning spaces may differently impact student outcomes compared to formal settings (Cross, 2011).

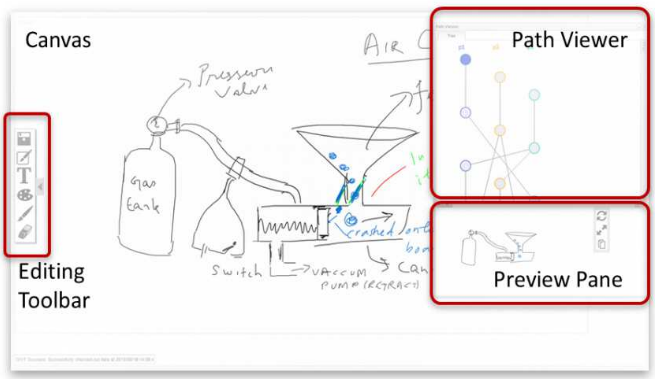
Commons area environment. Half of the teams were assigned to the commons area environment, which simulated informal working environments that are rich in ambient noise. Tables and chairs were arranged around a large open area of a building, near an elevator, offices, an atrium, and informal couch seating. This setting was selected to resemble open and informal learning spaces.

Private room environment. The remaining teams were assigned to work in a more formal setting--a private conference room furnished with a conference table and chairs. This setting was used to simulate working environments that are formal, private, and have less ambient noise.

Material context. Teams were assigned to use one of two sketching tools: paper or the skWiki sketching application on touch-based tablet devices.

Paper sketching tool. In the paper sketching context, participants created design sketches using paper and pen tools. Participants were given access to a stack of paper and various pens to use during sketching. During the design process, to share their sketches with team members, participants either held up the paper or passed the paper to others to visually communicate their idea. This paper sketching condition was set up to resemble the early-stage group engineering design practices that take place in many academic and industry engineering settings.

SkWiki sketching tool. In previous work, researchers have developed and studied the skWiki collaborative sketching environment, an open source application designed to facilitate sharing and elaboration of visually represented (i.e., sketched) ideas during collaborative design sessions. As shown in Figure 2, the skWiki interface is a web-based application on touch-based tablets (i.e., iPads). Using capacitive-touch styli, users can create design sketches on the skWiki interface and share the sketches with other team members through a shared space enabled by a back-end server, which stores and synchronizes the design sketches generated by all team members. This shared space is shown to the user via the Path Viewer, which records the progression of ideas and modifications made to shared sketches. Any team member can select from the shared sketches and modify or elaborate designs on their individual sketching tablet. For example, when a designer sees a design idea sketched by another team member, the designer can tap on the sketch through the Path Viewer and elaborate or edit the sketch in the Canvas window to converge to or diverge from specific design ideas. Thus, elaboration and manipulation of shared representations is readily accessible, and the affordances provided by the skWiki



sketching tool have the potential of enhancing collaboration outcomes (MASKED).

Figure 2. The skWiki sketching interface on a multi-touch tablet platform. Students use a stylus to sketch design ideas and then can share the sketches with the team through a shared space enabled by a back-end server. This shared space is shown to the user via the Path Viewer, a representation of the progression of ideas and additions made to shared sketches. Any team member can select from the shared sketches and then modify or elaborate designs on their individual sketching tablet.

Measures

Social interaction dynamics. In order to gauge participants interaction dynamics during the collaborative design sessions, we used wearable sociometric sensors to capture real-time data on a set of non-linguistic social signals (Olguín et al., 2009). The sensors are encased in a rectangular plastic badge, slightly smaller than an index card and about half an inch thick, and worn around the neck. The badges include a combination of sensors technologies including Bluetooth and infrared sensors, an accelerometer, and microphones, to capture a number of variables about speech and conversation dynamics, body movement and posture, and social proximity. The built-in algorithms allowed the sensors to calculate data on a series of sociometric measures that allow us to quantify social interaction dynamics. In this study, we focused on the four measures of conversation dynamics: Turn-Taking, Successful Interrupts, and Speech Overlaps (generated directly from the sociometric sensors), as well as Cyclic Index, a measure calculated from time series analysis of speech participation data. We define and operationalize these measures in Table 1.

Table 1
Sociometric Measures of Conversation Dynamics

Measures	Definitions	Operationalization	Data
Turn-taking	The number of turns speaker A took after another speaker B; the italicized text is an instance of speaker A taking a turn in response to other speakers.	Speaker B: It is just like a board game. *Speaker A: Yes, and we can add real action figures in.*	Turn-taking is recorded as a total frequency number for each participant during the entire session
Successful interrupts	A successful interruption is defined as speaker A starting to speak while speaker B is speaking, resulting in B falling silent while A continues to speak; the italicized text is an example of speaker A successfully interrupted speaker B in the middle of speech.	Speaker B: I think we can also add a ladder in the 3-D board game, so that… *Speaker A: oh, then the action figures can climb up the ladders.*	Successful interrupts is recorded as a total frequency number for each participant during the entire session
Speech overlap	Overlap occurs when one participant speaks at the same time as another participant in the group. The duration of speech that speaker A and B uttered simultaneously.	Speaker A: This looks great. So we choose this design as our final design. Speaker B: (simultaneously starts speaking just as A finished the word "This") I really like this idea a lot.	Speech overlap is recorded as a total frequency number for each participant during the entire session
Cyclic index	Cyclic patterns of how speakers engage in entrained and synchronized social interaction rhythms. Larger cyclic indices imply higher levels of entrainment among speakers.	The average amount of variance explained by the four largest and significant periodogram components in the four sets of 15-minute segments of each participant's speech participation data.	Cyclic index is obtained from time series analysis of the speech participation data, which is recorded as the average per second ratio of a participant's speech activity to the total amount of speech in the group.

Collaboration quality (α = .90)**.** To assess the quality of collaboration perceived by team members, we used a 12-item Likert-type scale, with ratings ranging from 1 (*inadequate*) to 5 (*excellent*) for each item. The items were adapted from a scale for collaboration readiness in scientific teams (Mâsse et al., 2008), and asked students about the ease of sharing ideas, communicating, accommodating different styles, resolving conflicts, and productivity during the session. This survey was administered at the end of the design session. The total score of the Collaboration Quality scale, with a range from 12 to 60 points, was used in the analysis.

Flow (α = .91)**.** An 8-item scale was created to assess task engagement, or creative *flow*, derived from Arici (2008). Csikszentmihalyi (1990) defines flow as an experience during the high-challenge and high-skill moments while performing autotelic or intrinsically-motivated tasks (Nakamura & Csikszentmihalyi, 2002). Drawing from extant literature on task engagement (Deater-Deckard, Chang, & Evans, 2013; Skinner & Belmont, 1993), the flow scale included three dimensions: *cognitive* (e.g., whether the activity was challenging), *behavioral* (e.g., whether they were actively involved), and *affective* (e.g., whether participants enjoyed the task, found it exciting). Items were measured on a 5-point Likert scale ranging from 1 (*not at all*) to 5 (*very much*) and administered at two time points: once in the middle and once at the end of the design session. The average of the flow total scores collected at the two time points, which ranged from 8 to 40 points, was used in the analysis.

Creative fluency. Creativity in divergent and idea generation tasks is often defined as the fluency or the number of new ideas generated by individuals or teams, and higher fluency is associated with higher creativity outcomes (Charyton & Merrill, 2009; Guilford, 1967; Paulus, 2000). In this study, we operationalized creative fluency as the total number of new sketches created by each participant. Based on previous work on creativity in engineering design

(Charyton, Jagacinski, & Merrill, 2008), a new sketch was counted towards an individual's measure of creative fluency when it showed originality in design ideas. For example, a new sketch that adds two lines to elaborate the details of a toy car was not counted as a new sketch. In contrast, if a sketch changed the function of the toy car and made it into a wearable and inflatable car shaped toy, then it was counted as a new sketch. The identification of new design sketches for creative fluency was coded by two people with a background in engineering design research. The reviewers first marked the new design sketches individually and compared the ratings at the end. Consensus was reached through discussion.

Procedures

Participants were randomly assigned to work on design tasks in one of the four Material x Spatial conditions: skWiki+Commons, Paper+Commons, skWiki+Private, Paper+Private (The descriptions of the conditions are presented in Table 2), and wore sociometric badges throughout the session. During the design session, each team was instructed to select a toy and identify the play value of the toy using the play pyramid and scales of play method (Kudrowitz & Wallace, 2010). All teams participated at the same time, thereby controlling variability in the environment. The *play value* is a concept that helps designers to understand and envision how users may interact with toys. The participants learned about these concepts in lectures prior to the study and were given reference pages describing the play pyramid and scales of play during the task. After determining the play value, participants were instructed to redesign the toy to change its play value so that users could play with the toys in a different manner. The redesign process required participants to brainstorm in groups and use engineering design techniques such as SCAMPER as well as "crossing products" (see Michalko, 2006). Each participant was asked to sketch their design ideas and collaborate with the team to create a final design idea.

Table 2

Description of the Four Design Conditions

Material Context	Spatial Context	
	Commons area	Private Room
skWiki	Participants worked in groups in an open commons area and each student used a stylus to sketch their design ideas or build on others' ideas on the skWiki application.	Participants worked in groups in a closed conference room and each student used a stylus to sketch their design ideas or build on others' ideas on the skWiki application.
Paper	Participants worked in groups in an open commons area and each student used pencils to sketch their design ideas or build on others' ideas on paper.	Participants worked in groups in a closed conference room and each student used pencils to sketch their design ideas or build on others' ideas on paper.

In the Paper teams, participants drew their sketches with pen and paper. Each participant was provided with sheets of numbered papers for identification, and a box of multicolored fine-tipped markers. To simulate paper-based collaborative design sessions in real settings, participants were instructed to collaboratively design the toy, but were not given explicit instructions regarding how to share their design sketches with one another. Thus, participants decided how they collaborated in the group.

In the skWiki teams, participants used styluses to sketch on the touch-based tablets using the skWiki application that allowed synchronization of design sketches across the team (More information about the skWiki tool is presented in Material Context under the Design Context section). Using the skWiki application interface, participants could view and also build upon or modify a teammate's sketches and generate new design ideas. Due to the novelty of the skWiki application, participants in this condition were given a brief 10-minute training session on the use of the skWiki tool prior to the study.

Finally, participants in all four conditions selected the most promising design idea through discussion. The process of generating multiple ideas and then selecting the most promising ideas combining both creative and analytical processes, known as Laseau's funnel (Laseau, 1980), was previously introduced to the students through lectures. The design session lasted for approximately 60 minutes. At the end of the session, the participants completed the collaboration quality scale and the flow scale. The flow scale was also administered mid-session to capture fluctuations in the participants' perception of flow.

Data Analysis

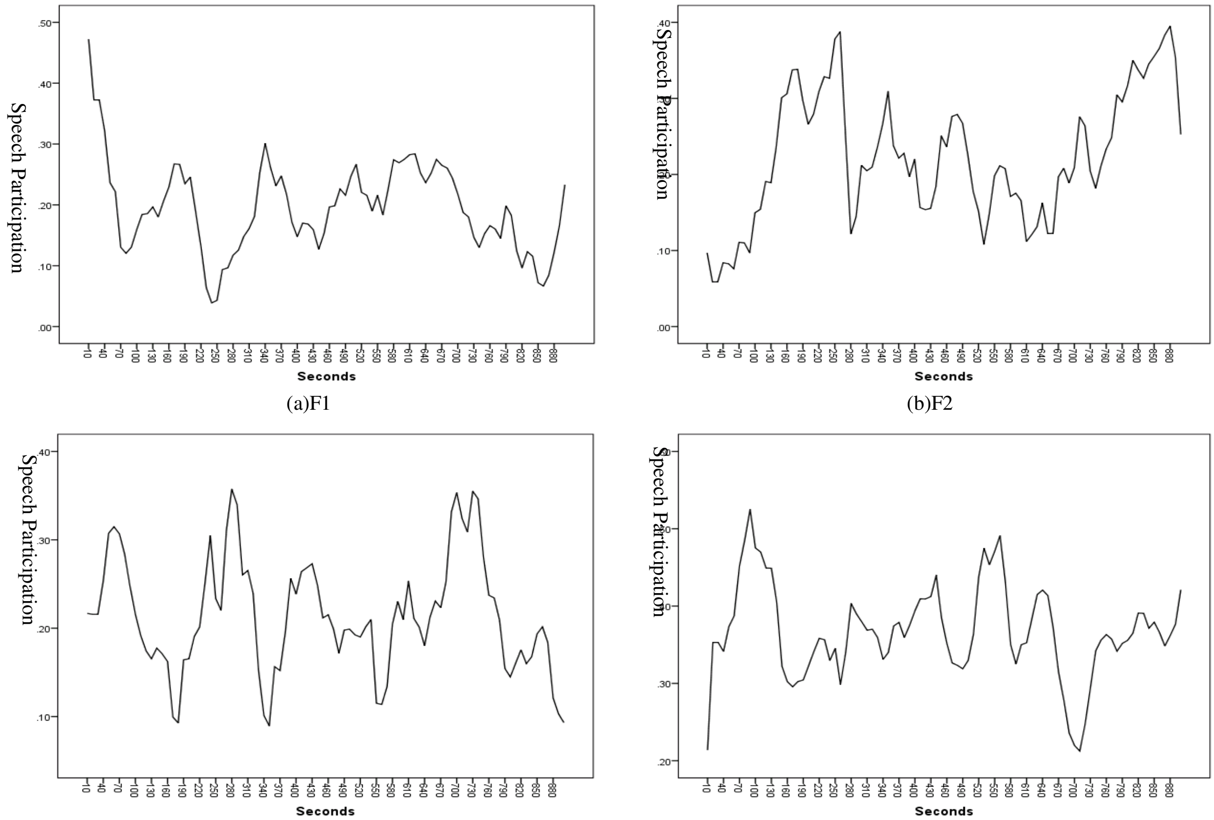
Processing Social Interaction Dynamics Data

Our research questions concern the roles of the social interaction dynamics in predicting collaboration quality and creative fluency. To obtain the social interaction dynamics data, we first extracted the total frequency count data on Turn-taking, Successful Interrupts, and Speech Overlaps from the sociometric sensors. We also extracted the second-by-second speech participation data for each participant from the sociometric sensors and conducted time series analysis to calculate the cyclic index.

Time series analysis and cyclic index. Previous research has found that speech participation in social interaction tends to show periodic rather than linear patterns, where speakers may coordinate and entrain each other's vocal activity to achieve synchronized rhythms (Chapple, 1970; Warner, 1992). Such cyclicity has been suggested as a fundamental organizing principle of social interaction (Chapple & Lui, 1976). Using time series methods, a spectral analysis in the form of periodogram analysis can identify the cyclic tendencies in such time series data and reveal patterns in how speakers engage in entrained and synchronized social interaction rhythms.

Conducting spectral analysis on speech participation time series data has been used widely in social interaction research (McGarva & Warner, 2003; Warner, 1992). For example, Warner (1992) conducted periodogram analysis on the speech participation time series data during a 40-minute conversation session, and calculated an index of cyclic patterns. Warner found that the cyclic index in the later 10-minute segment was significantly higher than that of the early 10-minute segment, suggesting that the speakers' interactions become more mutually entrained as interaction progresses. In this study, we draw on this literature on the cyclicity of social interaction and apply the periodogram analysis on speech participation time series data to identify synchronized processes in design teams' social interaction patterns.

Recall that in our study, speech participation for each participant was recorded on the sociometric sensors as second-by-second time series data. Because previous research suggests that cyclicity in social interaction tends to occur between three to six minutes (Warner, 1992; Warner, Malloy, Schneider, Knoth, & Wilder, 1987), we aggregated the individual participation data into 10-second intervals. Then, following the method used in Warner (1992) for vocal activity time series analysis, we divided the time series data into four 15-minute segments, each consisting of 90 observations ten seconds in length, thus yielding four segments of n=90 observations for each participant. Figure 3 illustrates an example of the raw time series data for the first 15-minute segment of Team F, who used the Private meeting room with the skWiki tool.



(a)F1 (b)F2

(c)F3 (d)F4

Figure 3. The time-series of the first 15-minute speech participation data of participants F1, F2, F3, and F4 from Team F (Private meeting room with skWiki tool). Speech participation was measured once every second by the sociometric sensor and aggregated as an average for every 10 seconds in the analysis. N=940 observations.

Finally, we conducted spectral analysis, in the form of periodogram analysis on each 15-minute segment. The periodogram analysis functions by partitioning the variance in the time series and examining the amount of variance accounted for by each of the N/2 or 45 periodic components. As discussed above, in each 15-minute segment, there are N=90 observations, yielding 90/2=45 components (Box, Jenkins, & Reinsel, 2013). The 45 periodic components ranged in cycle lengths of 10*(90/i), where 10 is the 10 seconds interval and i=1, 2,3,…45. Thus, the 45 periodic components corresponded to cycle lengths of 900s, 450s, 300s, 250s,…, and 20s

(Box et al., 2013). The percentage of variance explained by each periodic component can be calculated by dividing the periodogram value (the pdgm column in Table 3) by the total periodogram value of all periodic components. If the time series data are random or the "white noise" null hypothesis is true, then each periodic component would account for 1/45 or 2.22% of the overall variance of the time series. However, if there are one or more periodic components that account for much larger proportions of the variance, which is the case in this study, the time series can be considered approximately sinusoidal and demonstrating cyclic patterns (Warner, 1992).

To identify the most significant periodic components in the time series, we used Fisher's test (Russell, 1985). According to the Fisher's significance table, at the 0.05 significance level, in time series with 90 observations, the primary or the largest periodic component should account for more than 15% of the variance in the time series, the secondary or the second largest component more than 10%, the tertiary component more than 8%, and the quaternary component more than 7%. The recommended approach for analysis is to include only participants who have at least one significant periodogram component (Warner, 1992). In this study, all participants had at least one significant periodogram components, and therefore all participants were included. Table 3 shows an example of the output from the periodogram analysis for the first 15-minute speech participation data for participant F1. In this example, the periodic components at 70 seconds explains the highest percentage of variance (pctpdg=28%) and is significant at the 0.05 level, followed by periodic components at 30 seconds (pctpdg=20%), 40 seconds (pctpdg=15%), and 60 seconds (14%).

Table 3

Excerpt of the Periodogram Analysis Output for Participant F1's first 15-minute Speech Participation Data

Seconds	Speech Participation	Frequency	Period	pdgm	pctpdg*	spectral
10	0.47245	0		0	0	0.20067
20	0.37255	0.01053	95	0.01608	0.04	0.18055
30	0.37255	0.02105	47.5	0.08426	0.2	0.16761
40	0.3214	0.03158	31.66667	0.06413	0.15	0.22443
50	0.23644	0.04211	23.75	0.00314	0.01	0.32673
60	0.22178	0.05263	19	0.05683	0.14	0.24475
70	0.13041	0.06316	15.83333	0.11838	0.28	0.18087
80	0.12047	0.07368	13.57143	0.00228	0.01	0.18345
90	0.13078	0.08421	11.875	0.00025	0	0.13483
100	0.1596	0.09474	10.55556	0.00572	0.01	0.02203
110	0.18431	0.10526	9.5	0.0082	0.02	0.04007
120	0.18575	0.11579	8.63636	0.00558	0.01	0.04547

Note: *pctpdg represents the percentage of variance explained by the corresponding frequency or periodic components in the time series. This table shows an excerpt of the original output for participant F1. Due to space limit, the data between 130 seconds and 450 seconds are omitted in this table but are included in the calculations for cyclic index.

Using the methods described in Warner (1992), the Cyclic Index was obtained by first calculating the total amount of variance explained (the pctpdg value in Table 3) by the four largest and significant periodogram components in each 15-minute segment. We then averaged the variance across the four 15-minute segments to generate the mean Cyclic Index for each participant (Table 4 shows the descriptive statistics of Cyclic Index). The mean Cyclic Index reveals the tendency of synchronized cycles among speakers, where larger cyclic indices imply higher levels of entrainment among speakers (McGarva & Warner, 2003; Warner, 1992).

Predictive Models of Collaboration Quality and Creative Fluency

To answer the research questions on the roles of the material context, spatial context, and social interaction dynamics in predicting collaboration quality and creative fluency, we built two models using Partial Least Squares Regression (PLSR). The PLSR method builds regression models to predict the dependent variables (Y) through extracting latent structures from a set of independent variables (X) which are best for explaining X and predicting Y (Abdi, 2010). This method has been found to be especially useful for building predictive models because it extracts (non-observable) latent structures that "collect most of the variation of the real X (observable) variables in such a way that they may also be used to model the Y response (dependent) variables." (Mateos-Aparicio, 2011, p. 2308). PLSR was originally developed to address research questions during the early stages of theory development, where "low information" in theoretical specification and a limited number of available observations may result in multicollinearity among the independent variables (or more independent variables than observations) (Sosik, Kahai, & Piovoso, 2009; Wold, 2004). Compared to multilinear regression methods, the PLSR method has several advantages in that it values soft distributional assumptions, has lower requirements for sample size, and produces higher accuracy in parameter estimation in studies where large samples are difficult to obtain (Esposito Vinzi, Chin, Henseler, & Wang, 2010). The PLSR method allowed us to explore the relationships between predictors and response variables in our early stage of theory development and overcome the challenges of obtaining large sample sizes in collaborative engineering design settings.

In building the two predictive models for Collaboration Quality and Creative Fluency, we initially selected seven model predictors based upon the literature: Material Context, Spatial Context, Flow, and the four social interaction variables, Turn-taking, Successful Interrupts, Overlaps, and Cyclic Index (Dong, Lepri, Kim, Pianesi, & Pentland, 2012; Gaver, 1996; Johri &

Olds, 2011; Nakamura & Csikszentmihalyi, 2002; Sadler, Ethier, Gunn, Duong, & Woody, 2009; Warner, 1992). We next examined the distribution of the two response variables, and confirmed that the Collaboration Quality and Creative Fluency variables had symmetric distributions, eliminating the need for data transformation (Mateos-Aparicio, 2011). Regardless, the PLSR still performs scaling and centering for each predictor variable to ensure that the variables have an equal opportunity to influence the model (Sawatsky, Clyde, & Meek, 2015).

We built two PLSR models using the NIPALS (Non-linear Iterative Partial Least Squares) algorithm (de Jong, 1993; Mevik & Wehrens, 2007), regressing the seven predictors on Collaboration Quality and Creative Fluency. In fitting the model, the two categorical variables were coded as dummy variables: Material Context (0=skWiki, 1=Paper) and Spatial Context (0=Private room, 1=Commons area). To identify the best fit model with the least number of factors to explain the maximum amount of variance in the predictors and responses variables, we then employed four additional steps to refine the specification of the model: a) First, we used the Leave One Out cross-validation method, which checks how well a model will generalize to new data by conducting *n* iterations of training and testing to fit the predictive model. In each iteration, all but one observation *(i.e., n-1)* is used as the training set to train the model, which is then used to predict the test set—the one left out observation. This training and testing process continues until each observation has served as the testing set once; b) next, we examined the VIP (variable importance for the projection) statistics, which is the weighted sum of squares of the weights (Wold, 1995), and adopted a criterion of 0.8 as a cutoff point for predictor selection (Wold, 1995); c) additionally, we examined the regression coefficients of the predictors and excluded those with both small VIP and small regression coefficients; d) finally, we examined the factor loadings of each variable and excluded those with low factor loadings.

Results

To answer the research questions on the role of the material and spatial context and social interaction dynamics in predicting collaboration quality and creative fluency, we built two predictive models using Partial Least Squares Regression with seven predictors. Table *4* shows the descriptive statistics of the variables in the predictive models.

Table 4

Descriptive Statistics of the Predictor and Response Variables

	Variables	M	SD
Predictor Variables			
	Turn-Taking	1157.44	465.91
	Successful Interrupts	545.00	292.018
	Overlap	1065.78	372.71
	Flow	31.53	6.24
	Cyclic Index (%)	67.75	7.40
Response Variables			
	Collaboration Quality	50.06	4.58
	Creative Fluency	3.88	2.28

Note: The predictor variables also include Material Context and Spatial Context, which are categorical and are thus not included in this descriptive statistics table.

Predicting Collaboration Quality

Our first research question asked whether spatial and material contexts and social interaction dynamics can predict collaboration quality in design teams. Regressing all seven predictors (Turn-Taking, Successful Interrupts, Overlap, Flow, Cyclic Index, Material Context, and Spatial Context) on Collaboration Quality, the Leave-one-out Cross Validation method of the PLSR model recommended six factors for inclusion in the model: according to the predicted residual sum of squares (root mean PRESS) statistics for each factor, the appropriate number of factors for the model is when the lowest PRESS value is achieved (Abdi, 2010; Roy & Roy, 2008). The model summary indicates that the best model fit is achieved using six factors (RM PRESS=.99), where 94.69% of the variance is explained for the predictors and 61.97% of the variance is explained for the Collaboration Quality response variable (See Table 5). Note that the number of factors in PLSR refers to the latent factors extracted from the predictors. Therefore, six latent factors may represent the variation of multiple predictors in the model (Cox & Gaudard, 2013; Mateos-Aparicio, 2011).

Table 5

Leave-one-out Cross Validation (using NIPALS Algorithm) Modeling Collaboration Quality

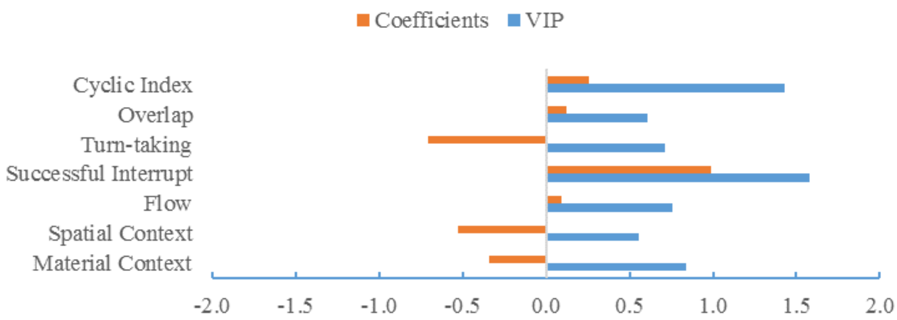
# factors	Root Mean PRESS	vdVT^2	Prob > vdV T^2	R^2X	Cum. R^2X	R^2Y	Cum. R^2Y
0	1.07	0.26	0.66	0.0000	0.0000	0.0000	0.0000
1	1.02	0.08	0.80	0.2237	0.2237	0.4220	0.4220
2	1.08	0.53	0.54	0.2258	0.4495	0.0761	0.4981
3	1.11	1.78	0.21	0.1431	0.5926	0.0656	0.5637
4	1.07	1.57	0.24	0.1199	0.7125	0.0455	0.6092
5	1.02	0.87	0.40	0.0963	0.8088	0.0187	0.6279
6	0.99	0.00	1.00	0.1159	0.9247	0.0045	0.6324
7	1.00	0.26	0.64	0.0753	1.0000	0.0024	0.6348

Model Summary

N	Factors	Var. X	Var. Y	VIP >0.8
16	6	94.69	61.97	3

Notes: vdV T^2=van der Voet T^2; Var. X = variation explained for cumulative X; Var. Y = variation explained for cumulative Y.

To select the predictors that are important for the model, we examined the VIP statistics for each predictor, using a criterion value of 0.8 as a cutoff point for predictor selection (Wold, 1995). As shown in Figure 4, Material Context, Cyclic Index, and Successful Interrupts have VIP values greater than 0.8, suggesting inclusion in the model. Additional evaluation of the standardized regression coefficients indicates other important contributors to the model. As suggested in previous research, during model specification it is important to consider both the VIP and standardized coefficient: predictors with VIP values lower than 0.8 can be retained if their coefficients are comparable to predictors with greater VIP values (Sawatsky et al., 2015). In Figure 4, we graphed VIP values against the standardized coefficient values, and found the VIP values for the other four predictors (Turn-taking, Spatial Context, Flow, and Overlaps) were lower than 0.8, but their standardized coefficients are comparable to those with higher VIP values. Therefore, all seven predictors were retained as predictors in the model. As shown in Table 5, retaining 7 predictors, the percent of variance in the Y variable accounted for by the latent factors, or R^2 =63.48%, indicating good strength in predicting observed values for both creative fluency and collaboration quality (Hair et al., 2011; Henseler et al., 2009).



	Material Context	Spatial Context	Flow	Successful Interrupt	Turn-taking	Overlap	Cyclic Index
Coefficients	-0.34	-0.53	0.09	0.99	-0.71	0.12	0.26
VIP	0.8	0.6	0.8	1.6	0.7	0.6	1.4

Figure 4. The Variable Importance for the Projection (VIP) and Standardized Regression Coefficient for centered and scaled data for each predictor of Collaboration Quality.

From Figure 4, we can see that Material Context, Successful Interrupts, and Cyclic Index are the strongest predictors of perceived Collaboration Quality. To verify the predictive power of the model, we generated a series of predicted response values for Collaboration Quality using the fitted model. Using methods recommended in previous research, we conducted a visual examination of the predicted score and the observed score, and confirmed that the model has a good fit and has high level of accuracy for predicting the data (see Figure 5) (Cox & Gaudard, 2013; Sawatsky et al., 2015).

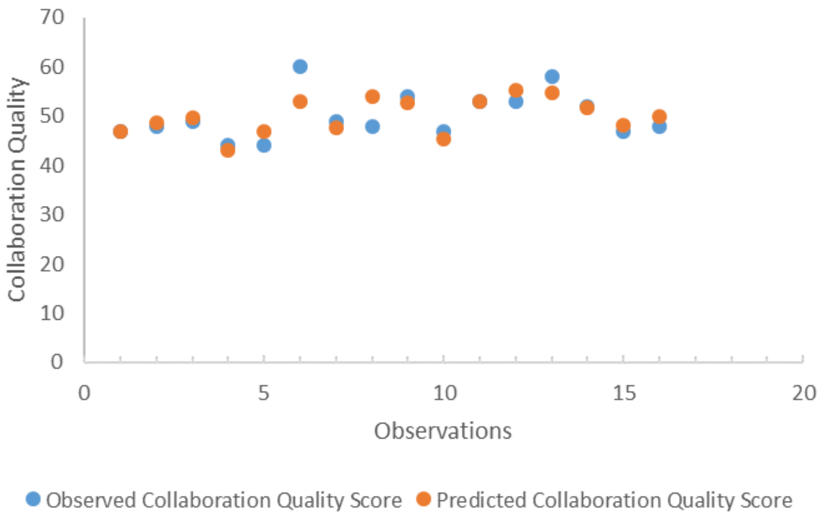


Figure 5. Predicted vs. observed Collaboration Quality values based on the fitted model. The vertical axis represents the Collaboration Quality ratings. Each mark on the horizontal axis corresponds to a participant. The orange dots represent the predicted Collaboration Quality rating using the predictive model. The blue dots represent the observed value—the actual collaboration rating of each participant.

Context. The results indicate a negative influence on Collaboration Quality for the Material and Spatial Context variables, indicating that the skWiki tool and the private space were more favorable for Collaboration Quality ratings. That the skWiki tool provided positive support for sketching during the design process is consistent with previous research indicating the advantages of computer-supported collaborative tools during design and brainstorming processes (Martínez, Collins, Kay, & Yacef, 2011). That the private spatial context was a more positive influence compared to the commons area context, was an unexpected finding and counters emerging research suggesting that open, informal spaces are more conducive to creative collaboration (Becker & Sims, 2001; Horgen, 1999; Kim & de Dear, 2013; Lerdahl, 2001; Stryker, 2004).

Flow. The results indicate that Flow positively predicts Collaboration Quality, consistent with group creativity and flow theories (Csikszentmihalyi, 2014; Nakamura & Csikszentmihalyi, 2002; Sawyer, 2008), which predict the positive affect that emerges when teams are well engaged with their task and peers (Amabile, 1996; Amabile, Barsade, Mueller, & Staw, 2005).

Interaction dynamics. Successful Interrupts, Cyclic Index, and Speech Overlaps yielded positive coefficients, indicating that increased entrainment or synchrony of team members is associated with higher Collaboration Quality ratings, consistent with our earlier research (MASKED). However, the model estimated a negative coefficient for turn-taking, a measure of verbal reciprocity during interaction (MASKED), perhaps indicating that reciprocal conversations that elaborate or build upon the ideas of others may hinder perceived collaboration quality (Mckinlay, Procter, Masting, Woodburn, & Arnott, 1994). This finding suggests that reciprocity in collaborative design settings using collaborative tools may differ from traditional conversational dyads or groups and suggests that more frequent turn-taking in computer-supported collaborative design does not necessarily lead to enhanced perceptions of collaboration quality. In summary, synchronous conversation dynamics, but not reciprocal turn-taking are associated with positive collaboration quality.

Predicting Creative Fluency

Our second research question asked whether spatial and material contexts as well as social interaction dynamics, are predictive of creative fluency in design teams. Using PLSR and the Leave-one-out cross validation method, we regressed Spatial Context, Material Context, Successful Interrupts, Overlap, Turn-taking, Flow, and Cyclic Index on Creative Fluency. According to the predicted residual sum of squares (PRESS) statistics, the appropriate number of latent factors corresponds to the lowest PRESS value (Abdi, 2010; Roy & Roy, 2008). As shown in Table 6, the smallest PRESS value is achieved for one latent factor, where 20.41% of the variance was explained for the predictors and 62.15% of the variance was explained for Creative Fluency. Note that the number of factors in PLSR refers to the latent factors extracted from the predictors. Therefore, one latent factor may represent the variation of multiple predictors in the model (Cox & Gaudard, 2013; Mateos-Aparicio, 2011).

Table 6

Leave-one-out Cross Validation (using NIPALS Algorithm) Modeling Creative Fluency with 7 predictors

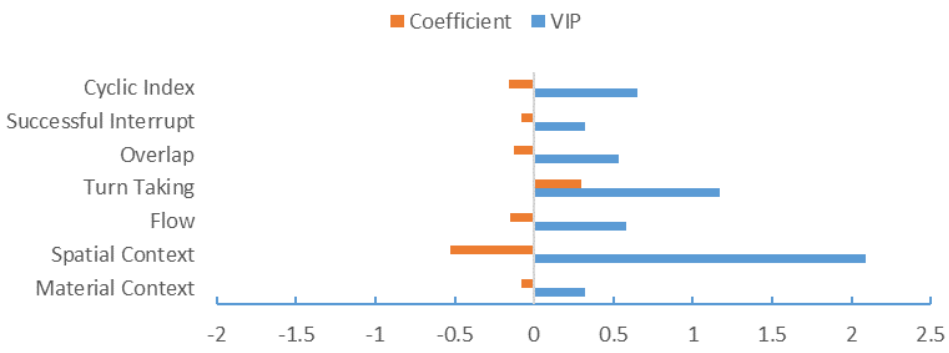
# factors	Root Mean PRESS	vdV T^2	Prob > vdV T^2	R^2X	Cum. R^2X	R^2Y	Cum. R^2Y
0	1.07	1.67	0.21	0.0000	0.0000	0.0000	0.0000
1	0.90	0.00	1.00	0.2163	0.2163	0.6197	0.6197
2	1.13	0.65	0.69	0.1611	0.3774	0.0448	0.6645
3	1.31	1.04	0.44	0.1822	0.5596	0.0131	0.6776
4	1.44	1.58	0.06	0.1466	0.7062	0.0075	0.6851
5	1.51	1.76	0.03*	0.1190	0.8252	0.0049	0.6900
6	1.52	1.85	0.01*	0.1430	0.9681	0.0005	0.6905
7	1.52	1.95	0.01*	0.0319	1.0000	0.0002	0.6907

Model Summary

N	Factors	Var. X	Var. Y	VIP >0.8
16	1	20.41	62.15	2

Notes: vdV T^2=van der Voet T^2; Variation X = variation explained for cumulative X; Variation Y = variation explained for cumulative Y.

Next we referenced the VIP statistics to select the predictors important for the model, using 0.8 as a criterion (Sawatsky et al., 2015). The results indicated that Spatial Context and Turn-taking have VIP values greater than 0.8. Graphing the VIP values against the standardized regression coefficients (Figure 6) revealed that while the VIP values of Overlap and Cyclic Index were lower, they have strong coefficients. In addition, because the NIPALS algorithm identified one latent factor for the model, we also examined the factor loadings (Table 7) of each predictor, which indicated that the Material Context factor carries important loading and may contribute to the model.



	Material Context	Spatial Context	Flow	Turn Taking	Overlap	Successful Interrupt	Cyclic Index
Coefficient	-0.08	-0.53	-0.15	0.3	-0.13	-0.08	-0.16
VIP	0.32	2.09	0.58	1.17	0.53	0.32	0.65

Figure 6. VIP and standardized coefficients for centered and scaled data for 7 predictors for Creative Fluency.

Table 7

The factor loading of each predictor for Creative Fluency

Predictor	Factor loading
Material Context	0.21
Spatial Context	0.78
Flow	0.17
Turn Taking	-0.50
Overlap	0.21
Successful Interrupt	0.10
Cyclic Index	0.30

Based on these three criteria (VIP, coefficient, and factor loading), we removed the Successful Interrupts factor from the model because it had the weakest set of VIP, coefficient, and factor loading values. Then we refit the model with the six remaining predictors. As shown in Table 8, the new model explained 24.00% of the variance in the predictors and 60.96% of variance in Creative Fluency. The VIP and standardized coefficients of the model with 6 predictors (Spatial Context, Material Context, Overlap, Turn-taking, Flow, and Cyclic Index) remained stable, and are visualized again in Figure 7. Spatial Context and Turn-taking remain the strongest predictors in this model, with VIP values greater than 0.8 (Sawatsky et al., 2015).

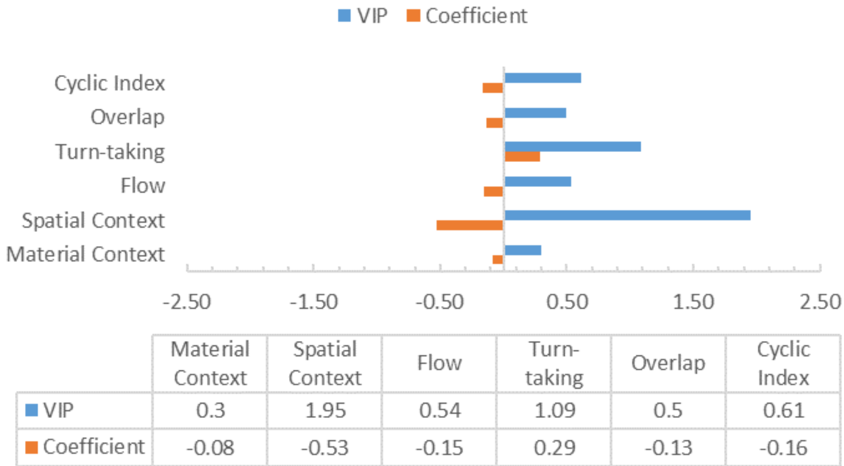


Figure 7. VIP vs coefficients for centered and scaled data with 6 predictors for Creative Fluency.

Table 8

Leave-one-out Cross Validation (using NIPALS Algorithm) Modeling Creative Fluency with 6 Predictors

# factors	Root Mean PRESS	vdV T²	Prob > vdV T²	R²X	Cum. R²X	R²Y	Cum. R²Y
0	1.07	2.86	0.10	0.0000	0.0000	0.0000	0.0000
1	0.84	0.00	1.00	0.2519	0.2519	0.6086	0.6086
2	1.20	0.97	0.51	0.1885	0.4404	0.0432	0.6518
3	1.31	1.14	0.30	0.1798	0.6203	0.0109	0.6628
4	1.41	1.31	0.14	0.1278	0.7482	0.0035	0.6664
5	1.50	1.48	0.03*	0.1190	0.8672	0.0015	0.6680
6	1.45	1.52	0.02*	0.1327	1.0000	0.0002	0.6682

Model Summary

N	Factors	Var. X	Var. Y	VIP >0.8
16	1	24	60.96	2

Notes: vdV T²=van der Voet T²; Variation X = variation explained for cumulative X; Variation Y = variation explained for cumulative Y.

As shown in Table 8, retaining 6 predictors, the percent of variance in the Y variable accounted for by the latent factors, or R^2 =66.82%, indicating good strength in predicting observed values for both creative fluency and collaboration quality (Hair et al., 2011; Henseler et al., 2009). After fitting the model, we generated a series of predicted response values for Creative Fluency from the model, and a visual examination and the fitted lines of the predicted and observed values are very similar, confirming the fit of the model (Figure 8) (Cox & Gaudard, 2013; Sawatsky et al., 2015).

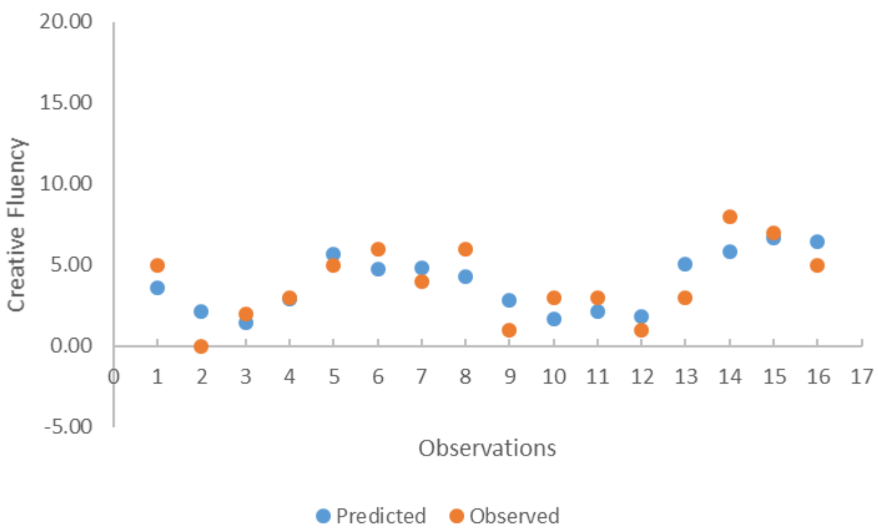


Figure 8. Predicted vs. observed Creative Fluency values based on the fitted model. The horizontal axis shows the 16 observations; the vertical axis shows the Creative Fluency count. The blue dots represent the predicted values generated from the model; the orange dots show the observed values of Creative Fluency.

Context. The results indicate a strong negative influence on Creative Fluency from Spatial Context, suggesting that the private environment was more favorable for creative fluency.

The contribution of the Material Context was slight, suggesting a positive advantage to using the skWiki collaborative tool compared to paper tools.

Flow. There was also a small negative relation between Flow and Creative Fluency in the design process. Considering that Flow was an average from two survey probes during the session, more frequent data collection intervals may be needed to capture fluctuations in flow throughout the design session.

Interaction dynamics. The positive association of Turn-taking with Creative Fluency supports earlier research that reciprocity is indicative of team members becoming more cooperative in their behaviors, which leads to better creative outcomes (MASKED). More specifically, because reciprocity is indicative of team members building upon or elaborating on others' ideas, these findings provide strong support for theoretical suggestions that elaboration is a process that directly enhances group creativity (Csikszentmihalyi, 2014; Sawyer, 2008). In contrast, the small negative association of Successful Interrupts and Cyclic Index with Creative Fluency suggests that synchronicity with other team members has less influence on creative idea fluency and may even have a slight inhibitory effect. This might be explained by the fact that synchronicity creates stronger shared mental models and fewer independent ideas, thereby reducing the quantity of unique ideas generated.

Discussion

This study demonstrates that the material and spatial context of design and the social interaction dynamics during collaborative design are significant predictors of both creative fluency and collaboration quality in engineering design tasks. These findings provide evidence that the design environment has an important relationship to collaborative outcomes; the dynamics of interactions during the design process, as measured in turn-taking, cyclic index, and successful interrupts, are also significant predictors of creative and collaborative outcomes. Building on prior research, our study extends the understanding of computer-supported collaborative design by demonstrating that in collaborative engineering design settings where multiple modalities of information are present, and verbal interactions and visual representations of sketching activities permeate the design space, different spatial and material contexts interact with and must be considered in parallel with how social interaction dynamics facilitate collaborative design quality and fluency.

In addition to providing empirical evidence on the dynamics of collaborative processes in computer-supported environments, these findings provide important theoretical contributions to our understanding of the context and interaction elements of situative learning theory (Johri & Olds, 2011; Stahl, Koschmann & Suthers, 2006), extend theorizing about the materiality of learning (Sørensen, 2009), introduce novel methodological approaches to studying collaborative learning processes, and offer practical contributions to understanding learning among high-level engineering designers and designing learning environments to facilitate collaborative creativity. In the following sections, we discuss the theoretical implications of context and interaction for situative learning theory, and then conclude with a discussion of the methodological and practical implications and future work.

The Role of Context and Interaction Dynamics in Collaboration Quality

Design context. The finding that the use of skWiki material tools and private spaces predicts higher ratings of collaboration quality highlights the important roles of the material and spatial context in the design setting. This finding is consistent with previous research in computer-supported learning environments, where the use of technology-enhanced tools and environmental factors lead to changes in collaboration outcomes (Martinez-Maldonado et al., 2017; Shen et al., 2008). In terms of material context, as situative learning theory suggests, while working in computer-supported design platforms designers not only interact with the digital material representations (e.g., sketches) created by oneself, but also interpret the digital cues and artifacts generated by others in the environment (Sørensen, 2009). Thus, a possible explanation for this finding is that while participants using paper tools had to sketch design ideas from scratch, participants using the skWiki tool could reference design ideas from their teammates in a shared electronic space and build upon these ideas. While one might argue that participants using paper sketching can examine each other's sketches and elaborate these designs on paper, when we examined the sketches from paper condition and the video tapes of the design sessions, we found that none of the participants in the paper condition shared or built upon others' sketches. Furthermore, in the paper condition we did not specify how the participants were to collaborate. Therefore, the fact that none of the participants in the paper conditions chose to collaborate or build upon others' ideas was noteworthy and may suggest the importance of computer-supported platforms to scaffold collaborative design.

In addition, the technological affordances of the skWiki tablets may encourage participants to examine others' ideas and elaborate their sketches, thus promoting positive attitudes towards the collaborative design process. In contrast, participants in the paper conditions were more individually focused on generating and sketching their own ideas and paid less attention to collaborative meaning making and idea generation. Therefore, this finding extends situative learning theory in engineering design learning contexts by emphasizing the importance of the materiality of learning (Sørensen, 2009) and highlights the benefits of computer-supported tools for collaborative design outcomes.

Regarding the spatial context, the finding that collaborative design in private rooms, compared to commons areas, is more predictive of positive collaboration quality outcomes contradicts previous findings which suggest that open, flexible, and informal environments may be more conducive to collaborative outcomes (Becker & Sims, 2001; Horgen, 1999; Kim & de Dear, 2013; Lerdahl, 2001; Stryker, 2004). Considering that collaboration quality was measured as the ease of sharing ideas, resolving conflicts, and team productivity, it is possible that in design tasks requiring cognitive effort and contribution, the private space is more conducive to group cohesion and collaboration. For example, Mehta and colleagues (Mehta, Zhu, & Cheema, 2012) have demonstrated that high levels of ambient noise in open workspaces increases processing difficulty (See also Nagar & Pandey, 1987; Weinsteln, 1974) and can also impair creativity, even though moderate levels of noise can be beneficial for highly creative individuals (Toplyn & Maguire, 1991). Situative learning theory tells us that the physical arrangement of a design environment can facilitate or suppress certain interactions or behaviors depending on the participants' interpretation of the environment (Jordan & Henderson, 1995; Leander, Phillips, & Taylor, 2010; Zerella et al., 2017). Thus, the simplicity of the private room environment may have provided fewer distractions or cues for the participants to interpret, compared to the more complex commons environment, thus lowering the cognitive demand on participant interactions and promoting collaborative outcomes.

Therefore, our finding contributes to literature on spatial contexts for collaborative design by showing that in environments involving computer-supported technology tools for engineering design, collaborative outcomes may be benefitted by more private spatial contexts. In addition, previous research has suggested that in collaboration projects that span over long periods of time, team members rated open and informal spaces as more effective for collaborative communication and productivity (Mishra, Mishra, & Ostrovska, 2012). However, this study suggests that when a collaborative design task is time-constrained, that is, an outcome is expected in a few hours rather than over a period of days, private spaces may be more beneficial.

Interaction dynamics. There were two important findings regarding how interactional processes of the design teams contribute to collaborative quality: a) that levels of synchronicity positively predict better ratings of collaboration quality, and b) that levels of reciprocity negatively predict such ratings. First, all three indicators of synchronicity (interrupts, overlaps, and cyclic index) were found to be positively associated with collaboration quality. Successful Interrupts occur when a participant interrupts another's speech and is allowed to proceed to express her ideas without the other finishing their speech. This form of interruption is viewed as a positive indicator of synchronization in conversation, similar to two people finishing one another's conversations when they share common frames of mind (Giles, Coupland, & Coupland, 1991; Giles, Mulac, Bradac & Johnson, 1987; Tannen, 1989). Similarly, Cyclic Index is also indicative of synchronicity, or entrainment, among speakers in social interactions (Warner, 1992). Therefore, the findings from this study are consistent with research demonstrating the benefit of synchronicity among group members to perceptions of the collaboration process (McGarva & Warner, 2003; Warner et al., 1987). As shown in previous research, social interaction in computer mediated environments follows non-linear and cyclical patterns, which are deemed essential to the maintenance of group cohesion and collaborative quality (Sudweeks, 2004). However, the specific patterns of these speech dynamics, among multiple groups and over an extended time period in different technical and spatial contexts, have not yet been well studied. Our findings build on this research by providing micro-level evidence, at the process level, that synchronicity in conversational dynamics positively predicts perceived collaboration quality, an element theoretically important in collaboration theories.

In contrast, turn-taking, an indicator of reciprocity in social interaction, was found to be negatively associated with perceived collaboration quality. Turn-taking occurs when a participant follows another participant's conversational turn and is indicative of reciprocal interaction (MASKED). This finding contradicts previous results from Curhan and Pentland (2007), where turn-taking dynamics were positively associated with collaboration outcomes. One possible explanation of this difference is that the use of collaborative support tools that allow designers to convey their ideas materially (i.e., sketching) as well as discursively (i.e., talking), may change the importance of discourse in idea generation and elaboration, and its relationship to collaboration quality. This result suggests the necessity to provide training for engineering designers in attending to, interpreting, and engaging with teammates verbally, even while interacting materially with multiple material and digital artifacts.

The Role of Design Context and Interaction Dynamics in Creative Fluency

Design context. The spatial and material context variables were found to positively predict creative fluency, with the skWiki tool and private space contexts contributing to positive creative fluency. This finding is consistent with previous research where the use of collaborative support tools and environmental factors lead to better creative outcomes (Martinez-Maldonado et al., 2017). We believe the material affordances of the skWiki tool provide specific advantages by encouraging designers to examine and elaborate others' ideas and sketches to generate new design ideas. Additionally, the skWiki platform supports parallel use of materials so that team members can view and edit multiple ideas simultaneously, thereby facilitating more fluent generation of design ideas. This is consistent with previous findings where the use of collaborative multi-touch tools helped designers to share digital representations and engage in the co-construction of design ideas (Martinez-Maldonado et al., 2017). In contrast, students using paper sketching tools may focus more individually on their own sketches, which may replicate ideas being sketched by others. Thus, the finding that the material context positively predicts creative fluency may arise from the fact that the skWiki tool provides a shared creative space where team members scaffold each other's ideation and design process.

Similarly, because of the differences in technological affordances of sketching and sharing, participants in the skWiki tool condition did not have to make additional efforts to present their ideas to others or check if their ideas were accepted by other members (MASKED), whereas participants sketching on paper relied upon verbal interaction to present and share their design ideas with the group. In addition, paper sketches were constrained in the ability to be shared and simultaneously edited by others, thereby creating a material bottleneck that could restrict elaboration and subsequent generation of ideas (MASKED).

Thus, the skWiki collaborative support tool facilitates a more parallel, versus sequential, processing and generation of design ideas. It is also possible that the skWiki tool facilitates creative fluency because the platform allows team members to easily share and build upon ideas created by all members without relying on their ability to verbally persuade the acceptance of their ideas (e.g., being an effective and persuasive communicator to help the team to see the value of the idea). Thus, technology-enhanced sketching environments may broaden opportunities for both implicit (visual) and explicit (verbal) sharing and adopting of ideas in design settings, thus promoting creative outcomes.

The private spatial context was more beneficial for creative fluency than the commons area. This finding is consistent with previous research that identified physical arrangements in learning environments as influential for performance (Roth et al., 1999). Also important is that the participants in this study primarily remained seated during the design session, whereas students in previous studies were engaged in tasks that involved movement in spaces around focal stations (Roth et al., 1999; Leander et al., 2010). Despite the possibility that design processes with limited motion in space may restrict the impact of the physical arrangements and environment of collaborative design teams, spatial context was still an important predictive factor. Therefore, in future studies we will examine design spaces and tasks that involve broader movement around and interaction with different types of spatial environments to examine in more depth the influence of spatial contexts.

Interaction dynamics. Our results indicate that turn-taking, an indicator of reciprocity in social interaction, was significantly and positively associated with creative fluency. This finding is consistent with previous research indicating that turn-taking provides confirmation of response during interaction, leading to performance benefits (Olguin & Pentland, 2010).

However, levels of synchrony or entrainment (cyclic index and speech overlaps) were found to be negatively associated with creative fluency. This finding provides empirical evidence, at the process level, that synchronous interaction influences idea generation and elaboration, a construct theoretically important in both creativity and collaboration theories. However, that higher levels of synchrony were associated with less fluency in idea generation contradicts previous findings suggesting synchrony benefits performance (Olguin & Pentland, 2010).

The difference between our findings and those of previous studies can be attributed to the variations in design tasks. While previous studies investigated collaborative tasks that did not include material activities such as sketching (Olguin & Pentland, 2010), the design tasks in the current study required participants to transition between visual and verbal forms of discourse. We know that engineering design teams rely on both verbal and non-verbal discourses to construct and share design ideas (Ariff, Badke-Schaub, & Eris, 2012; Purcell & Gero, 1998; Reid & Reed, 2005). As a result, participants who are more verbally engaged (and synchronous) may be less likely to be materially engaged in generating sketches. However, it is possible that creativity is enhanced through team synchronicity in ways other than fluency in idea generation. For example, positive social affect has been found to be positively related to creative thoughts in self-reported daily personal narratives (Amabile et al., 2005). Thus, it is possible that synchronicity may have led to changes in the participants' internal creative thought processes rather than externalized creative productions. Therefore, we posit that this finding does not suggest that higher synchrony in conversation dynamics are negative factors in creative design performance. Rather, this finding implies the need to consider the challenges posed by multimodal information that are specific to collaborative design tasks, as well as the need to provide training for engineering students to adjust to the demands from both verbal and non-verbal information representations.

Another potential explanation for this difference in finding is that while previous studies focused on collaboration in traditional pen-and-paper settings, the current study included a collaborative design tablet for sketching. It is possible that while working on tablets, students' attention to sketching on new technology platforms and attending to synchronize with others' comments competes for cognitive load and impedes design sketching performance (Kreijns et al., 2002). For example, there are challenges in showing affirmative signals of openness to others' ideas in face-to-face computer collaborative settings, which can lead to the suppression of innovative ideas (Thompson & Lordan, 1999). As a result, participants engaged in high verbal synchrony might have felt diverted rather than scaffolded in meaning construction and failed to execute the ideas through sketching, thereby lowering the quantity of sketched ideas. Researchers have proposed potential ways to address such challenges in computer-supported collaborative settings, including providing scripted interaction and other training strategies to promote social interaction quality (Fischer et al., 2007; Adamson, Ashe, Jang, Yaron, & Rosé, 2013). Our finding suggests the need to explicitly instruct designers in appropriate ways to exhibit supporting attitudes and provide effective scaffolding towards group members.

In summary, this study showed that social interaction dynamics are significant predictors of creative collaborative outcomes across different material and spatial contexts in engineering design. These findings highlight the important role of social interaction dynamics in collaborative engineering design settings, where students simultaneously engage with both verbal interaction and non-verbal interactions such as sketching to build design ideas.

At the same time, the differential findings regarding social interaction dynamics, such as reciprocity being positively associated with creative fluency but negatively associated with collaboration quality, and synchrony being positively associated with collaboration quality, cautions against a series of "whole part" notions that all social interaction dynamics are positive contributors to creative collaboration and that team members should be encouraged to be active participants in verbal interaction regardless of the purpose and context.

Findings from the current study are especially meaningful to learning in material-rich contexts such as engineering and technology, where meaning is embedded within and constructed through interaction with both human agents as well as material artifacts. Developing model interaction and collaborative learning practices within such hybrid multi-modal and technology rich environments requires a consideration of the impact of social interaction dynamics that are specific to engineering design settings. In these cases, rather than scripting interaction towards more frequent turn taking dynamics, the more beneficial interaction dynamics may be oriented towards fostering an optimal negotiation of balancing the verbal and visual elements of design, or simply talking and sketching behaviors.

Limitations

The study has limitations in sample size and population. The study was integrated as part of an engineering design class where the students were included as study participants. Although this sample is reflective of students who have prior knowledge in engineering design and sketching, the sample may pose challenges in regards to sample size and the generalizability of the results to other populations, such as design professionals. However, the use of partial least squares regression has been found to be effective in identifying predictive models where such traditional linear regression methods assumptions as sample size and collinearity are violated, which provides confidence that the findings from this study have practical significance in the real-world application. The implementation of the study also contributed to the limitations. In two of the four experiment conditions, students were asked to work on touch-based tablets to sketch design ideas. Considering that students are traditionally trained in paper sketching platforms, the digital platform may pose challenges for some students, despite the training they received prior to the experiment sessions. These limitations indicate that cautions must be taken while generalizing the findings.

Conclusions and Future Work

This study established two models for predicting collaboration quality and creative fluency outcomes based upon material and spatial context variables, as well as social interaction dynamics. The use of continuous real-time sociometric measures introduces an innovative approach to examine the interaction processes of engineering teams and their influence on collaborative learning outcomes. We see a natural extension of this study into future research efforts from at least three aspects, including: (1) designing technology-rich environments to facilitate creative collaborative design based on our findings of the key predictors of collaboration quality and creative fluency; (2) using controlled experiments to identify causal relations between the predictors and the collaborative design outcomes; and (3) studying the interaction of verbal and non-verbal interaction dynamics during collaborative design.

Regarding designing technology-rich environments that are suitable for collaborative design, the next step extending from the current study would be to involve professional designers in authentic spatial and material contexts to provide real-time feedback for design teams based on patterns in social interaction dynamics. For example, using wearable technology and mobile applications, we can collect real-time data on conversational turn taking dynamics, and generate visual feedback on mobile display platforms to periodically inform team members about adjusting their conversation dynamics to be more conducive to design collaboration outcomes. This kind of intervention has been previously suggested and examined for group dynamics in organizational settings (Pentland, 2012).

Based upon the findings from our predictive models in this study, we also intend to conduct experimental studies to identify causal relationships between conversation dynamics and collaborative design outcomes. Specifically, by manipulating the social dynamic frequencies in design teams using technology-enabled real-time interaction mediators (e.g., encourage or redirect students’ talk based on the interaction patterns), we can begin to identify causal relationships between the different types of social interaction dynamics and creative collaboration outcomes in design teams.

The findings of this study provide an important contribution to research in the field of computer-supported collaborative design, by focusing on process-level dynamics of collaborative teams, allowing us to extend understanding of the emergence and development of learning in engineering design learning teams situated in particular contexts. This finding has implications for understanding the predictive role of conversation dynamics in successful collaborative practices in engineering design learning, across spatial and material contexts. Specifically, computer-supported collaborative environments in engineering design contexts demand special consideration of the unique interaction patterns required during design collaboration, where participants must contend with sharing design knowledge both verbally and visually. Understanding how to balance and negotiate the multiple demands of collaborative sharing modes in order to maximize collaboration quality or creative fluency outcomes, extends our theoretical and practical understanding of group creativity and collaborative design. Ultimately, these findings can lead researchers to identify optimal balance in collaborative dynamics that are conducive to engineering design outcomes.

Acknowledgement

This work is supported by National Science Foundation grant [grant no. omitted for review].

References

ABET (2014). 2015-2016 Criteria for accrediting engineering programs. Retrieved from http://www.abet.org/accreditation/accreditation-criteria/criteria-for-accrediting-engineering-programs-2015-2016/#objectives

Adamson, D., Ashe, C., Jang, H., Yaron, D., & Rosé, C. (2013). Intensification of group knowledge exchange with academically productive talk agents. In *Proceedings of the 10th International Conference on Computer Supported Collaborative Learning*.

Amabile, T. M. (1996). *Creativity in context*. Boulder, CO: Westview Press.

Arici, A. (2008). *Meeting kids at their own game: A comparison of learning and engagement in traditional and 3D muve educational-gaming contexts*. Doctoral dissertation, Indiana University, Bloomington.

Ariff, N. S. N. A., Badke-Schaub, P., & Eris, O. (2012). Conversations around design sketches: Use of communication channels for sharing mental models during concept generation. *Design and Technology Education: An International Journal, 17*(3), 27–36.

Astin, A. W. (1993). The climate for undergraduate engineering education: results from a recent national study. *Address presented at the Annual Engineering Dean's Institute, New Orleans*.

Awang, H., & Ramly, I. (2008). Creative thinking skill approach through problem-based learning: pedagogy and practice in the engineering classroom. *International Journal of Human and Social Sciences*, *3*, 18-23.

Barron, B. (2006). Interest and self-sustained learning as catalysts of development: A learning ecology perspective. *Human development*, *49*(4), 193-224.

Brereton, M., Cannon, D., Mabogunge, A., & Leifer, L. (1996). Collaboration in design teams: mediating design progress through social interaction. In N. Cross, K. Dorst, & H. Christiaans (Eds.), Analysing design activity. Wiley

Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher, 18*(1), 32–42.

Bucciarelli, L. (1994) *Designing engineers.* Cambridge, MA: The MIT Press.

Charyton, C., Jagacinski, R. J., & Merrill, J. A. (2008). CEDA: A research instrument for creative engineering design assessment. *Psychology of Aesthetics, Creativity, and the Arts*, *2*, 147.

Chartrand, T. L., & Bargh, J. A. (1999). The chameleon effect: The perception-behavior link and social interaction. *Journal of Personality and Social Psychology, 76,* 893–910.

Charyton, C., & Merrill, J. A. (2009). Assessing general creativity and creative engineering design in first year engineering students. *Journal of Engineering Education*, *98*, 145-156.

Clancey, W. J. (2009). Scientific antecedents of situated cognition. In P. Robbins & M. Aydede, (Eds.), *The Cambridge handbook of situated cognition* (pp. 11–34). New York, NY: Cambridge University Press.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences.* Hillsdale, NJ: Erlbaum.

Cross, J. (2011). *Informal learning: Rediscovering the natural pathways that inspire innovation and performance*. John Wiley & Sons.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience*. New York, NY: Harper and Row.

Curhan, J. R., & Pentland, A. (2007). Thin slices of negotiation: predicting outcomes from conversational dynamics within the first 5 minutes. *Journal of Applied Psychology, 92*, 802.

Deater-Deckard, K., Chang, M., & Evans, M.E. (2013). Engagement states and learning from educational games. In Fran C. Blumberg Shalom M. Fisch (Eds.), *Digital games--A context for cognitive development: New directions for child and adolescent development* No. 139 (pp. 21-30). John Wiley & Sons.

Delaherche, E., Chetouani, M., Mahdhaoui, A., Saint-Georges, C., Viaux, S., & Cohen, D. (2012). Interpersonal synchrony: A survey of evaluation methods across disciplines. *IEEE Transactions on Affective Computing, 3*(3), 349 – 365.

de Vries, E., & Masclet, C. (2013). A framework for the study of external representations in collaborative design settings. *International Journal of Human-Computer Studies*, *71*(1), 46–58.

Dillenbourg, P. (1996). Some technical implications of distributed cognition on the design on interactive learning environments. *Journal of Artificial Intelligence in Education*, *7*, 161-180.

Dillenbourg, P. (2005). Designing biases that augment socio-cognitive interactions. In R. Bromme, F. Hesse & H. Spada (Eds.), *Barriers and biases in computer-mediated knowledge communication--and how they may be overcome*. Dordrecht, Netherlands: Kluwer Academic Publisher.

Dong, A., Hill, A. W., & Agogino, A. M. (2004). A document analysis method for characterizing design team performance. *Journal of Mechanical Design*, *126*, 378-385.

Dong, W., Lepri, B., Kim, T., Pianesi, F., & Pentland, A. S. (2012). Modeling conversational dynamics and performance in a social dilemma task. In the *International Symposium on Communications Control and Signal Processing* (pp. 1-4).

Dourish, P. (2001). *Where the action is: The foundations of embodied interaction*. Cambridge, MA: MIT press.

Dul, J., & Ceylan, C. (2011). Work environments for employee creativity. *Ergonomics*, *54*, 12–20. doi:10.1080/00140139.2010.542833

Dul, J., & Ceylan, C. (2014). The impact of a creativity-supporting work environment on a firm's product innovation performance. *Journal of Product Innovation Management*, *31*, 1254–1267. doi:10.1111/jpim.12149

Dym, C. L., Agogino, A. M., Eris, O., Frey, D. D., & Leifer, L. J. (2005). Engineering design thinking, teaching, and learning. *Journal of Engineering Education*, *94*, 103-120.

Fayard, A.L. (2012). Space matters, but how? In Leonardi, P.M., Nardi, B.A., and Kallinkos, J. (Eds.), *Materiality and organizing: Social interaction in a technological world* (pp. 177-195). Oxford, UK: University Press.

Felder, R. M., Felder, G. N., & Dietz, E. J. (1998). A longitudinal study of engineering student performance and retention. V. Comparisons with traditionally-taught students. *Journal of Engineering Education*, 87, 469-480.

Fischer, F., Kollar, I., Mandl, H., & Haake, J. M. (2007). *Scripting computer-supported collaborative learning: Cognitive, computational and educational perspectives* (Vol. 6). Springer.

Gaver, W.W. (1996). Situating action II: Affordances for interaction: The social is material for design. *Ecological Psychology, 8*, 111–129.

Giles, H., Coupland, N., & Coupland, J. (1991). Accommodation theory: Communication, context, and consequence. In H. Giles, J. Coupland, & N. Coupland (Eds.), *Contexts of accommodation: Developments in applied sociolinguistics* (pp. 1 – 68). Cambridge, UK: Cambridge University Press.

Giles, H., Mulac, A., Bradac, J. J., & Johnson, P. (1987). Speech accommodation theory: The first decade and beyond. *Communication Yearbook, 10*, 13-48.

Greeno, J. G. (1989). A perspective on thinking. *American Psychologist, 44*(2), 134–141.

Greeno, J. G., Collins, A. M., & Resnick, L. B. (1996). Cognition and learning. In D. C. Berliner & R. C. Calfee (Eds.), Handbook of educational psychology (pp. 15-46). New York: Macmillan.

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods, 18*, 59-82.

Guilford, J. P. (1967). *The nature of human intelligence*. New York, NY: McGraw-Hill.

Hoffman, B., & Nadelson, L. (2010). Motivational engagement and video gaming: A mixed methods study. *Educational Technology Research and Development, 58*(3), 245-270.

Howard, T. J., Culley, S. J., & Dekoninck, E. (2008). Describing the creative design process by the integration of engineering design and cognitive psychology literature. *Design Studies*, *29*, 160-180.

Jeong, H. (2013). Verbal data analysis for understanding interactions. *The international handbook of collaborative learning* (pp.168-183). New York, NY: Routledge.

Johri, A., & Olds, B. M. (2011), Situated engineering learning: Bridging engineering education research and the learning sciences. *Journal of Engineering Education, 100*, 151–185. doi: 10.1002/j.2168-9830.2011.tb00007.x

Jordan, B., & Henderson, A. (1995). Interaction analysis: Foundations and practice. *The Journal of the Learning Sciences*, *4*, 39-103.

Kim, T., Chang, A., Holland, L., & Pentland, A. S. (2008). Meeting mediator: enhancing group collaboration using sociometric feedback. In *Proceedings of the 2008 ACM conference on Computer supported cooperative work* (pp. 457-466). ACM.

Koschmann, T. (2013). Conversation analysis and collaborative learning. *The International Handbook of Collaborative Learning* (pp.149-164). New York, NY: Routledge.

Kreijns, K., Kirschner, P. A., & Jochems, W. (2002). The sociability of computer-supported collaborative learning environments. *Educational Technology & Society, 5*, 8-22.

Kudrowitz, B.M., & Wallace, D. R. (2010). The play pyramid: a play classification and ideation tool for toy design. *International Journal of Arts and Technology, 3*, 36-56.

Laseau, P. (1980). *Graphic thinking for architects and designers.* New York, NY: Van Nostrand Reinhold.

Lave, J. (1991). Situated learning in communities of practice. In L. B. Resnick, J. M. Levine, & S. D. Teasley (Eds). *Perspectives on socially shared cognition* (pp. 63–82). Washington, DC: American Psychological Association.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge, UK: Cambridge University Press.

Lewis, L. K. (2006). Collaborative interaction: Review of communication scholarship and a research agenda. *Communication Yearbook, 30*, 197-247.

Looi, C., Wang, L., & Song, Y. (2013). Mobile computer-supported collaborative learning. *The international handbook of collaborative learning*, (pp.420-436), New York, NY: Routledge.

Mâsse, L. C., Moser, R. P., Stokols, D., Taylor, B. K., Marcus, S. E., Morgan, G. D., ... & Trochim, W. M. (2008). Measuring collaboration and transdisciplinary integration in team science. *American Journal of Preventive Medicine*, 35(2), 151-160.

Michalko, M. (2006). *Thinkertoys: A handbook of creative-thinking techniques*. Berkeley, CA: Ten Speed Press.

Miles, L. K., Nind, L. K., & Macrae, C. N. (2009). The rhythm of rapport: Interpersonal synchrony and social perception. *Journal of Experimental Social Psychology, 45,* 585-589.

Nakamura, J., & Csikszentmihalyi, M. (2002). *The concept of flow. Handbook of positive psychology*, 89-105.

Norman, D. A. (1993). Cognition in the head and in the world: An introduction to the special issue on situated action. *Cognitive Science, 17*(1), 1–6.

Olguín, D. O., & Pentland, A. S. (2008). Social sensors for automatic data collection. AMCIS 2008 Proceedings, 171.

Olguín, D. O., & Pentland, A. (2010). Assessing group performance from collective behavior. In *Proceedings of CSCW '10 Computer Supported Cooperative Work.*

Pahl, G., Beitz, W., Feldhusen, J., & Grote, K. H. (2007). *Engineering design: a systematic approach* (Vol. 157). Springer Science & Business Media.

Palou, E., Gazca, L., García, J. A. D., Lobato, J. A. R., Ojeda, L. G. G., Arnal, J. F. T., ... & Garibay, J. M. (2012). High-Quality Learning Environments for Engineering Design: Using Tablet PCs and Guidelines from Research on How People Learn. *International Journal of Food Studies*, *1*(1).

Paulus, P. B. (2000). Groups, teams, and creativity: The creative potential of idea-generating groups. *Applied Psychology: An International Review, 49*, 237.

Pentland, A (2012) The new science of building great teams. *Harvard Business Review, 90(4),* 60-69.

Prince, M. J., & Felder, R. M. (2006). Inductive teaching and learning methods: Definitions, comparisons, and research bases. *Journal of Engineering Education, 95*, 123-138.

Purcell, A. T., & Gero, J. S. (1998). Drawings and the design process: A review of protocol studies in design and other disciplines and related research in cognitive psychology. *Design Studies, 19*, 389-430.

Reid, F. J., & Reed, S. (2000). Cognitive entrainment in engineering design teams. *Small Group Research*, *31*, 354-382.

Reid, F. J., & Reed, S. E. (2005). Speaker-centredness and participatory listening in pre-expert engineering design teams. *CoDesign*, *1*, 39-60.

Roth, W. M. (1996). Art and artifact of children's designing: A situated cognition perspective. *Journal of the Learning Sciences*, *5*(2), 129-166.

Roth, W. M., McGinn, M. K., Woszczyna, C., & Boutonne, S. (1999). Differential participation during science conversations: The interaction of focal artifacts, social configurations, and physical arrangements. *Journal of the Learning Sciences*, *8*(3-4), 293-347.

Sawyer, R. K., & Greeno, J. (2009). Situativity and learning. In P. Robbins & M. Aydede (Eds.), *The Cambridge handbook of situated cognition* (pp. 347–367). New York, NY: Cambridge University Press.

Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: An historical perspective. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (pp. 409-426). Cambridge, UK: Cambridge University Press.

Shah, J.J., Smith, S.M., & Vargas-Hernandez, N. (2003). Metrics for measuring ideation effectiveness. *Design Studies,* 24, 111–134.

Shah, J. J., Vargas-Hernandez, N., Summers, J. D., & Kulkarni, S. (2001). Collaborative Sketching (C-Sketch)—An idea generation technique for engineering design. *The Journal of Creative Behavior*, *35*(3), 168-198.

Skinner, E. A., & Belmont, M. J. (1993). Motivation in the classroom: Reciprocal effects of teacher behavior and student engagement across the school year. *Journal of Educational Psychology, 85*(4), 571-581.

Suchman, L. A. (2007). *Human-machine reconfigurations: Plans and situated actions*. New York, NY: Cambridge University Press.

Taborda, E., Chandrasegaran, S.K., Kisselburgh, L., Reid, T., & Ramani, K. (2012). Enhancing visual thinking in a toy design course using freehand sketching. In *Proceedings of the ASME International Design Engineering Technical Conferences and Computers & Information in Engineering Conference* (267-276).

Tannen, D. (1989). *Talking voices: Repetition, dialogue, and imagery in conversational discourse*. New York, NY: Cambridge University Press.

Terenzini, P. T., Cabrera, A. F., Colbeck, C. L., Parente, J. M., & Bjorklund, S. A. (2001). Collaborative learning vs. Lecture/discussion: students' reported learning gains. *Journal of Engineering Education*, 90, 123-130.

Thompson, G., & Lordan, M. (1999). A review of creativity principles applied to engineering design. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, *213*(1), 17-31.

Tripathi, P., & Burleson, W. (2012). Predicting creativity in the wild: Experience sample and sociometric modeling of teams. In *Proceedings of CSCW '12 Computer Supported Cooperative Work*, Seattle, WA.

Van der Lugt, R. (2002). Brainsketching and how it differs from brainstorming. *Creativity and Innovation Management, 11*(1), 43-54.

Vaux, A. (1985). Variations in social support associated with gender, ethnicity, and age. *Journal of Social Issues*, *41*(1), 89-110.

Wiltermuth, S. S., & Heath, C. (2009). Synchrony and cooperation. *Psychological Science, 20,* 1-5.

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. *Science*, *330*(6004), 686-688.