

Predicting Creativity in the Wild:  
Experience Sampling Method and Sociometric Modeling of Movement and  
Face-To-Face Interactions in Teams

by

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## ABSTRACT

With the rapid growth of mobile computing and sensor technology, it is now possible to access data from a variety of sources. A big challenge lies in linking sensor based data with social and cognitive variables in humans in real world context. This dissertation explores the relationship between creativity in teamwork, and team members' movement and face-to-face interaction strength in the wild. Using sociometric badges (wearable sensors), electronic Experience Sampling Methods (ESM), the KEYS team creativity assessment instrument, and qualitative methods, three research studies were conducted in academic and industry R&D labs. Sociometric badges captured movement of team members and face-to-face interaction between team members. KEYS scale was implemented using ESM for self-rated creativity and expert-coded creativity assessment. Activities (movement and face-to-face interaction) and creativity of one five member and two seven member teams were tracked for twenty five days, eleven days, and fifteen days respectively. Day wise values of movement and face-to-face interaction for participants were mean split categorized as creative and non-creative using self-rated creativity measure and expert-coded creativity measure. Paired-samples t-tests [ $t(36) = 3.132, p < 0.005$ ;  $t(23) = 6.49, p < 0.001$ ] confirmed that average daily movement energy during creative days ( $M = 1.31, SD = 0.04$ ;  $M = 1.37, SD = 0.07$ ) was significantly greater than the average daily movement of non-creative days ( $M = 1.29, SD = 0.03$ ;  $M = 1.24, SD = 0.09$ ). The eta squared statistic (0.21; 0.36) indicated a large effect size. A paired-samples t-test also confirmed that face-to-face interaction tie strength of team members

during creative days ( $M = 2.69$ ,  $SD = 4.01$ ) is significantly greater [ $t(41) = 2.36$ ,  $p < 0.01$ ] than the average face-to-face interaction tie strength of team members for non-creative days ( $M = 0.9$ ,  $SD = 2.1$ ). The eta squared statistic (0.11) indicated a large effect size. The combined approach of principal component analysis (PCA) and linear discriminant analysis (LDA) conducted on movement and face-to-face interaction data predicted creativity with 87.5% and 91% accuracy respectively. This work advances creativity research and provides a foundation for sensor based real-time creativity support tools for teams.

Dedication

To Those Who Gave Me Wings To Fly

&

To Alyosha

(January 6, 2008- January 7, 2011)

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## Chapter 1

### INTRODUCTION

Creativity has been defined as any process, product, or person that is novel and appropriate (Mayer, 1999). This dissertation investigates the relationship between group activity characterized through team members' movement and face to face interactions within teams, and creativity. The relationship was investigated in research and development (R&D) teams in the industry and the academia. Group activity was tracked through sensor data from sociometric badges (Kim, Chang, & Pentland, 2007). A social science survey instrument KEYS (T. Amabile, 1996; T. M. Amabile, Conti, Coon, Lazenby, & Herron, 1996) was implemented through electronic Experience Sampling Method (ESM) (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) to capture self-reported creativity and was supplemented with expert-coded creativity measures. Statistical methods, machine learning, and qualitative approaches were used to analyze and validate the relationship between group activity (movement and face-to-face interaction) and everyday creative and non-creative events. The proposed framework paves the way for automated creativity support tools (CSTs) based on team activity.

#### **Everyday Creativity Comes to the Fore**

Creativity as a phenomenon has been of deep interest to scientists, philosophers, artists and policy makers. While research on creativity can be traced back to the Greek times (Aristotle, 350BC), Guilford's annual American Psychological Associations' presidential speech in 1950 marked the beginning of modern creativity research (Guilford, 1950). In the modern view, creativity is considered

to be a part of everyday life (Certeau, 1988). People recycle, adapt, or transform everyday objects in multiple ways for their benefit (Wakkary & Maestri, 2007; Wentworth, 2006 ). These everyday innovations can be conceptualized on a continuous creativity spectrum based on the degree of creativity they may express (T. M. Amabile, 1983; R. J. Sternberg & T. I. Lubart, 1995). Researchers distinguish everyday creativity from those of substantial creative contributions in a variety of ways. Gardner expresses range of creativity as ‘little C’ creativity as opposed to ‘big C’ creativity (Gardner, 1993). According to Gardner, while efforts of Einstein and Van Gogh can be said to possess ‘big C’ creativity, small creative efforts in everyday life are examples of ‘little C’ creativity. While there is some debate on the issue of what constitutes substantial contributions in creativity research, there is a widespread consensus that everyday creativity is a cognitive process that is part of core human make-up.

From the early days of computer science, there has been interest in researchers to simulate and understand human abilities through computational tools. In a similar vein, computers have been used to either simulate human creativity or support human creativity. The former promise of using computers to simulate human creativity (also called computational creativity) was heralded in the 1980s by the BACON system (Langley, Simon, Bradshaw, & Zytkow, 1987) that replicated the third law of Kepler (The square of the orbital period of a planet is directly proportional to the cube of the semi-major axis of its orbit.) automatically. More recently, the latter human-centric approach to creativity and computation has emerged. In the human-centric approach, taken up by Human



Computer Interaction (HCI) researchers (Burlison & Selker, 2002; Shneiderman, 2003), the aim is to create tools that promote and support human creativity.

In fact recent years have seen an increase in the research on creativity based on the human centric view. In 2002, Burlison and Selker (Burlison & Selker, 2002) convened a workshop at the annual conference of Computer-Human Interaction (CHI) and emphasized the connection between human creativity and computational interfaces and placed the user at the forefront. In 2007, a workshop on creativity support tools (Shneiderman et al., 2006) was attended by several prominent creativity and HCI researchers. Papers now appear regularly as part of leading international HCI conferences that address the issue of supporting creativity. The national science foundation in United States launched the CreativeIT initiative which recognized the need for research that focuses on the confluence of technology, arts as well as the unique role of information technology (IT) in advancing new understandings of creativity. While these initiatives have led to several key contributions in the field of creativity research, there are still gaps of knowledge that need to be filled on the issue of computational support for creativity. One such gap that this dissertation seeks to address lies in employing wearable sensors to model, sense and predict creativity of teams.

Recently, scientists have found novel ways to access nonverbal cues and subconscious states in human users through physiological and biometric sensing which includes skin conductance recording, voice tone recognition, facial

expression analysis, gesture and posture signals and geospatial behavioral tracking through location, movement, and network sensors (Pentland, 2008; Picard et al., 2004). Instruments advanced by the social sciences have also reflected the growth in understanding of creativity and a transition from appreciating creativity as a pure reasoning process to a more complex interactive spectrum within users' internal and external context (T. Amabile, 1996). With the use of wearable computing tools, there is an opportunity to collect multimodal data about human activities and interactions and use this data to model creativity, predict creativity, and support creativity through computational tools.

### **Wearable Sensor Based Approach to Group Creativity Research**

Computer science has aggressively advanced sensor based pattern recognition with applications such as face recognition (Turk & Pentland, 1991) and gait recognition (Lee & Grimson, 2002). Broadly, the goal of these techniques has been to detect a low level signal stream and recognize relevant patterns from it. Such recognition systems have been useful in a variety of application areas such as security and health. The underlying algorithms that process large quantities of multidimensional data have matured and computing solutions to complex recognition, prediction and analysis problems have been developed. However, since their widespread introduction in the 1990s, these computational systems have by and large not been mobile due to the lack of available computing power on mobile platforms at that time. Their sensors were installed at certain key locations and this information was transmitted to a central server, a little like a central nervous system connected with a mass of low level servers (Pentland,

2009). These fixed computing heavy approaches limited the use of such technology to study teams and groups which were highly mobile and dynamic.

With the rapid growth in mobile computing and sensor technology, it is now possible to access data from a variety of sources ("A special report on smart systems: A sea of sensors," Nov 4, 2010). With the increase in pervasive nature of sensors and their miniaturization, it is possible to develop wearable computing platforms where teams dynamics can be sensed in a continuous manner. However, researchers face new challenges with regards to advancing mobile computing methods and deploying sensors in the real world. A central theme that is now emerging as a major area of investigation in computer science lies in recognition and prediction of complex human behavior by analyzing sensor streams from mobile devices. A person's location, presence, physiology and environment (among other things) can now be captured through easily available smartphones. These smartphones are already an integral part of the human user and usage of these devices provides important clues about their human users (Pentland, 2009). Smartphone penetration in the world is poised to grow manifolds (Wikipedia, 2011). Given the opportunity that the current situation presents, it is important for researchers to investigate various facets of use of wearable technologies in studying human behavior.

Studying behavior has been of interest to researchers in anthropology, cognitive psychology and more recently to human computer interaction investigators. From a data collection setting and realism perspective, there are

traditionally two approaches in the study of human behavior. In the first approach, participants' behavior is studied in controlled conditions with experiments designed to induce a certain behavior and detailed protocols are used to precisely assess the variables. In the second approach, participants' behavior is studied in their natural environment (often termed as "in the wild" studies) with embedded human experimenters annotating and analyzing behavior. It was necessary for the experimenters to make difficult choices of methods that compromised generalizability to real environments on the one end by focusing the study of human groups within strict laboratory conditions and of compromising precision on the other end by employing ethnographic qualitative observations (McGrath, 1995). In the wild studies employ a combination of ethnographic observations, shadowing of humans, surveys and questionnaires to study human behavior. These in the wild methods of analysis have the best chance of accurately capturing human behavior due to their realism. Traditional use of the tools helps in collecting data that can be adequately used to model segments of human behavior limited to a particular individual and their activities. However, from a team behavior perspective, while the patterns generated through conventional qualitative tools may capture many aspects of the overall behavior, more often than not, certain key pieces of information may remain amiss. For example, observations gathered by a single observer may not be adequate to capture multiple activities occurring in a team at any instance of time. Theoretically, by increasing the number of observers in the environment it is possible to capture information about the activities in the environment from several perspectives.

However, more than two observers are often considered to be disruptive to capture naturalistic interactions. With such constraints imposed on data collection in complex environments, there is a need for an unobtrusive alternative that can augment existing methods of data collection and enable piecing together a more complete picture of behavior from an individual and team perspective. This is precisely where wearable sensors and mobile computing can enable a methodological contribution to in the wild studies.

Sensor based methods can provide the unobtrusive alternative to studying human behavior in the wild. I propose a mixed methods approach to studying human behavior. In this mixed-methods interdisciplinary approach, human user is equipped with the sensors “in the wild” that capture low level information on human behavior. This low level information is augmented with qualitative approaches such as ethnography to give rise to novel understanding of human behavior. The described human-centric multi-methodological approach can enable an improved understanding of the teams and inform the creation of sensor-rich environments that maximize the creativity of teams.

Some work has been done to investigate the feasibility of sensors and computational environments to support group work (Pentland, 2005, 2008). Eagle (Eagle, 2005) proposed that the team interaction sensors, behavior sensors and physiological sensors could be studied in combination with conventional qualitative methods to mine behavior of individuals and groups within their real world context. Termed as *reality mining* (Eagle, 2005; Pentland, 2009), it is an

interdisciplinary approach that combines social science methods with pattern recognition to give useful patterns of human and team behavior. To date, work in reality mining has been limited to studying team behavior in terms of productivity, efficiency and the impact of providing feedback on team performance on a teams' productivity (Pentland 2009). In this dissertation, I apply tenets of reality mining to study creativity within research teams. To develop such approaches, it is important to choose the appropriate wearable sensors that capture the required information in a seamless manner.

In order to analyze creativity through sensors, from a sensor design perspective, there are three research major challenges:

- 1) *Finding a comprehensive framework that maximizes the utility of the sensors for humans.* A key element of promoting use of sensors lies in providing a persuasive framework for human users to wear and utilize the sensors. This requires a careful design of the sensors' ubiquity to allow for a low physical profile of the sensors and a feedback mechanism from the sensors that is meaningful to the users and the community.
- 2) *Defining the nature and form of effective interactions between sensors and humans.* Interactions between sensor systems and humans need to be carefully choreographed to allow for a rich meaningful interaction experience. If sensors and interactions

are cumbersome, then humans are not likely to use the systems in the long term.

- 3) *Conducting empirical investigations into mutualism that involves benefits as well as limitations of both humans and technology.* Sensor technology should be designed to provide information that benefits teams directly and also seeks human input to improve its data analysis capabilities when needed.

In essence, study and creation of sensor enriched civilization is dependent on our understanding of the human user and the context within which he or she operates.

An interesting recent example of a device that meets the above criteria is the sociometric badge (Pentland, 2007). These badges are placed around the neck of the user to capture movement, speech, and location. They are a form of “environmentally aware computing” allowing capture of person’s location, presence, and elements of the environment (Pentland, 2005). This information can then be used to develop human-centered applications that motivate and facilitate human-environment and human-human relationships. In addition, these badges provide a customized platform for sensor based interfaces and applications that can provide feedback and support users. The level of feedback they can generate can be used to provide scaled functionality based on user expertise. The badges are easy to use, small in size and are ubiquitous in their nature. HCI research has leveraged such sensors using speech, and artifacts to study interactions within

members of groups (DiMicco & Bender, 2007; Farooq, 2007; Olguin Olguin, Gloor, & Pentland, 2009). Based on these factors, sociometric badges were chosen in this research, as an adequate platform to capture team behavior and link them to creativity.

As a part of my investigations, I apply a novel framework that combines existing qualitative methods of studying group creativity in context (T. M. Amabile, Barsade, Mueller, & Staw, 2005) with sensor-based data gathered with the means of a wearable computing tool. The goal is to link sensor data with human creativity. The research is done in naturalistic settings and aims to find the optimal use of sensor data toward supporting human creativity and team work. This dissertation makes a fundamental contribution in the methods for assessing the functions and needs of groups that can benefit from novel means of technological support for creative problem solving. I show through several studies reported in this dissertation that in many ways the world of sensors is synergistic with the world of humans and that empirical investigations into the nature of this relationship will ultimately lead to symbiotic socio-technical systems supporting creativity.

### **Creativity Support Tools**

While the work in this dissertation focuses on measurement and evaluation of creativity through sensors, it is important to consider the state of the art in creativity support tools (CST) to generate the requirements from a measurement tool. Such an understanding of CST would enable design, development and



evaluation of an effective measurement system that could seamlessly provide creativity support in the future.

In the workshop for creativity support tools (CST) (Shneiderman et al., 2006) sponsored by NSF, the attendees identified qualities of CSTs. In these qualities, an emphasis is placed on the structure of the creative production. The researchers offered a classification of CSTs into five non-exclusive categories

- a. low formality ad hoc interfaces free from restrictions,
- b. high flexibility interfaces that allows wide range of interactions,
- c. systems capable of providing detailed information on functioning of themselves,
- d. systems marked by the ease of selection and manipulation,
- e. systems characterized by high ceilings, low thresholds and wide walls meaning they provide facilities for advanced users, easy entry for novices, small well-chosen set of features that support wide range of features respectively.

While the above said characteristics embody some of the needs of the creative user, there are additional means that can be employed to maximize human creativity. In addition to the ease and flexibility of use, creativity support needs to be marked by following additional characteristics: (a) customization, (b) exploration, (c) accessibility, (d) utility, (e) aesthetics, (f) social embeddedness also known as context. It is argued that a successful CST will facilitate user's cognitive skills through effective behavioral feedback and reinforcement. These

characteristics are situated in the theory of intrinsic and extrinsic motivation that drives user's creativity (T. Amabile, 1996).

Motivation and engagement play an important role in the creative process (Russ, 1999). Research by Russ (Russ 1999) suggests that a creativity support tool needs to measure creativity effectively through a mixed methodology approach to gain a comprehensive understanding of creativity. The methodology must include both internal and external context of the user and then define methods based on this holistic understanding of creativity to positively impact creativity production. Some existing research suggests that this is a feasible goal. In fact, it has been shown that the interaction of physiological and behavioral variables and cognitive styles can be managed by enhancing awareness between and among group members. Higher self-awareness leads to self-directed adaptation of behavior (DiMicco & Bender, 2007). It may also allow higher attention to group's processes, goals, and strategies. West *et al.*. (West, Patera, & Carsten, 2009) defined this as reflexivity. This type of feedback is related to work by Gersick and Hackman (Gersick & Hackman, 1990) who found that work groups can break dysfunctional habitual routines by self-reflection. Similarly, a group's self-monitoring can enhance the understanding of breakdowns of creativity related to both cognitive or affective factors and lead to prevention of breakdowns (Farooq, 2007). Thus the underlying requirement for any measurement approach to succeed in the real world lies in effectively measuring creativity in context.

Several researchers have emphasized the role of context in creativity. Specifically researchers argue that creativity must be studied as a phenomenon that interacts with its environment. An example routinely cited is of the role of communication backchannels, such as vision, touch, and body language in our interactions with the real world and the limitations of lab based analysis of groupwork in capturing these communication backchannels. In recent years efforts have shifted from emphasizing communication support to supporting interaction as a whole: a paradigmatic change that further emphasizes the need for studying creativity in context. Now, there is a greater demand of tools and techniques that are able to adequately capture the physiological signals and social interactions of humans to advance human capacity to create and produce.

Another element of CST research that bears some influence on the work presented in this dissertation lies in design of the feedback mechanisms. Several types of CST's proposed by researchers either partially recognize, or promote the idea of supporting interaction through persuasion, monitoring, and feedback. The success of persuasive interfaces (Fogg, 2003) is a proof of the potential of this technology. Today users' needs go beyond words, and research is needed to adequately identify and model these needs and create design rationale for CSTs that guide the synergy between humans and computer. In other words, we need socially intelligent tools that allow emergent creativity. Allowing for persuasive feedback means we need both team centered and individual centered measures. This is a key requirement for creativity measurement architecture.

As a summary, we need to assess whether we can scientifically elucidate the relationship between the user's internal context with its environments through our measurement architecture. Then investigation is required to ascertain whether the measures can be sufficiently modeled to allow novel design rationales in human centered computing. In order to do this, we must first derive clear and concise definition of creativity and team interaction from existing literature. Then, we must look into models of each to understand and draw any connections between creativity and team interactions. Subsequently, we must empirically test the validity of this connection and fine-tune the creativity measures accordingly. For CST, we must be able to design interfaces that elucidate and exploit this relationship in order to give rise to emergent creativity clusters across users. In addition, we must generalize the role of these creativity support environs in different contexts and analyze their common and differing grounds with varying motivation, domain specificity, and requirements. We must be able to visualize the pros and cons of such interfaces. All of these activities require a method to study creativity in context and adequately link user's complex cognitive and behavioral variables with creativity.

By using a human-centric sensor based approach in conjunction with creativity research methodologies from the social sciences, this dissertation advances a framework that employs wearable sensor based information to understand individual and team creativity in context(T. M. Amabile et al., 1996). It employs sociometric badges (Pentland, 2007) to predict creative and non-creative days among team members, based on the movement and face-to-face

interaction of team members. Furthermore, it uses sensor based data to model creative and non-creative days within teams by using pattern recognition techniques. In the future, we can employ this wearable computing tools for team behavior management and feedback to foster creativity. Thus, the presented research lays the foundation for automated creativity support tools (CSTs) aimed at promoting creativity.

In this investigation, several long term studies (from two to four weeks) were conducted over two years on group creativity in leading research and development (R&D) laboratories. These laboratories had similar spatial environments. All were located within a room with cubicles facing the walls. All participants had regular working hours and the environment encouraged hands-on, real time interaction towards development of artifacts. To explore initial variable of interest, a pilot study was conducted consisting of five people over twenty-five days. This pilot study was conducted remotely and had limited experimenter involvement. Encouraged by the trends discovered in the pilot study, two further experiments were subsequently conducted with two, seven member teams for eleven and fifteen days in leading R&D labs. The goal was to study creative behavior of small groups in the wild (T. M. Amabile et al., 2005). A combination of daily online survey, cell phone based experience sampling methods, qualitative observations, and wearable sensing that detected movement and face-to-face interaction was used. The ultimate goal of this research is to develop activity (such as movement, and face-to-face interaction) based models of creativity that

can analyze and predict creativity by monitoring sensor data. This paves the way for sensor based real time creativity support tools for members in teams.

### **Organization Overview**

In Chapter 2, related work and background is discussed in relation to the proposed goals of the dissertation. Then, instruments that are used in the studies are presented in Chapter 3. Chapter 4 details the conceptual framework that informed the design of the experiments. Chapter 5, Chapter 6, and Chapter 7 present exploratory experiment, experiment 1, and experiment 2 respectively. Chapter 8 describes the computational modeling that predicts creativity. Chapter 9 provides a discussion and Chapter 10 presents conclusions highlighting the key contributions of this dissertation.

## Chapter 2

### LITERATURE REVIEW

#### **Major Approaches in the Study of Creativity**

There are many definitions for creativity but there is a consensus that creativity is creation of anything that is useful and original (Mayer, 1999). Gardner (Gardner, 1993) described creativity as “the human capacity to regularly solve problems or to fashion products in a domain, in a way that is initially novel but ultimately acceptable in a culture.” According to Csikszentmihalyi, creativity is a process that can be observed only at the intersection where individuals, domains and fields intersect (M Csikszentmihalyi, 1997). Amabile defines creativity as an idea or product that is novel and meaningful and a creative person as one that is capable of creativity (T. Amabile, 1996). Depending on one’s perspective taken of creativity, as property of a person, product, or process, researchers are divided over several of the basic questions on creativity as well as the best research approaches that are suitable for the study of creativity (Sternberg, 2007).

There are five main approaches to study of creativity (Mayer, 1999): (1) Psychometric (2) Experimental (3) Historiometric (4) Biographical (5) Biometric. Guilford’s test on creativity (Guilford, 1950) and Torrance Tests of Creative Thinking (Torrance, 1974) were some of the early psychometric efforts designed to measure either the personality traits or cognitive-affective tendency. These psychometric studies focus on personality and environmental correlates of creativity of product, process, or person. Since psychometric studies focus on

direct measurement of creativity, it suffers from problems such as that of internal validity (confusing measures of creativity with other constructs), external validity (generalization of tests), and predictive validity. Experimental approaches focus on experiment or quasi-experiments that isolate cognitive or problem solving aspects of creativity. Being conducted in laboratory settings, they tend to be high in precision but low on generalizability. Historiometric studies focus on historical data. Various historiometric studies have been conducted on topics such as eminence, musical creativity and invention. A variety of factors have been isolated and discussed in relation to creativity using historical data.

One of the famous approaches is that of biographical studies that focuses on qualitative analysis of specific individuals recognized to be highly creative and understanding the factors of creativity behind them. This method remains popular till today and is the basis of several popular science books. With recent advances in neurobiology and genetics, some researchers have started to focus on biometric studies of creativity that use technologies such as fMRI to understand the relationship between brain functions and cognitive functions. Sometimes researchers may combine two or more methodologies in order to strengthen their results. For example, it is not unusual to find a combination of biographical and historiometric approach to derive conclusion on factors of creativity.

The experimental studies on creativity focus on developmental, social, educational, cognitive, and emotional influences and aspects of creativity as their dependent variable. An experimental study will typically involve manipulation of



some variable prior to creativity or problem solving tasks and subsequently testing its effect on creative process or output. For example, Runco (Runco, 2004) found that explicit instructions can in fact be used to manipulate flexibility as well as appropriateness of solutions. Researchers have also tested matters of intuition where guesses were found to correlate with correct responses even when the participants were not sure (Bowers, Regehr, Balthazard, & Parker, 1990).

Experimental approaches have also been employed to study the relationship between affect and creativity. Most of these studies have focused on the self-report of varying types of emotional states such as happiness, excitement etc. The research then is geared towards linking physiological responses such as heart rate to emotional state and creativity. Some researchers have actively manipulated affective states in participants and tested their effect on creative problem solving (Isen, 1999; Russ, 1999). For example, Hoppe and Kyle (Hoppe & Kyle, 1990) manipulated the affective state by showing participants short movie clip containing images and sounds of personal loss and mourning and found that those exposed to the films tended to use more affect laden words and were less imaginative. Closely related to affect is the issue of intrinsic motivation. First discussed by MacKinnon (MacKinnon, 1965) as one the most prevalent traits in creative personality, several researchers have identified and supported the role of intrinsic motivation in the creative process (T. M. Amabile et al., 1996; M Csikszentmihalyi, 1997).

Study of creativity within the environmental context has been increasing rapidly (T. Amabile, 1996; R. J. Sternberg & T. Lubart, 1995) due to the arguments listed in Chapter 1. Creativity in context studies tend to identify the positive or negative impact of environmental and contextual factors such as availability of resources, work pressure and leadership style as well as intrinsic motivation and extrinsic motivation. As expected in these studies, the role of intrinsic motivation has emerged as a major factor. Supporters of intrinsic motivation take the view that creative expression is motivated by personal enjoyment and satisfaction and is not necessarily affected by direct external rewards or punishments of creative expression. In fact, in some cases of “in the wild” studies, external reward has been found to be deterrent to creative output. Overall the researchers propose that extrinsic award can only serve the purpose of engaging a person in a task (Russ, 1999). Too much extrinsic reward will discourage a person from risk taking behavior, encourage conformity and therefore hinder creativity. This is known as “intrinsic motivation hypothesis” proposed by Amabile (T. Amabile, 1983) and forms a cornerstone of her componential model of creativity in context (T. Amabile, 1996).

Componential model of creativity (T. Amabile, 1996) identifies three components of the creative performance: (1) domain relevant skills that are acquired either innately or by education, (2) creativity relevant skills acquired through training and dependent on personality, and (3) task motivation which involves minimization of influence of extrinsic motivation and maximizing intrinsic motivation. Like the componential model of creativity, Sternberg and

Lubart (R. J. Sternberg & T. Lubart, 1995) investment theory of creativity states that in some cases extrinsic motivation may serve to enhance intrinsic motivation. Woodman *et al.* (Woodman, Sawyer, & Griffin, 1993) interactionist model of creative behavior too identifies intrinsic motivation as a component conducive for creativity. Csikszentmihalyi (M Csikszentmihalyi, 1997) and Gardner (Gardner, 1993) include intrinsic motivation as a personality trait important for creativity. Intrinsic motivation has been talked about in the form of intense commitment to work, passionate involvement in problem solving, deriving pleasure in working, seeking challenges that match skill level, a psychological ‘high’ with heightened feelings of involvement and concentration (described as ‘flow’ by Csikszentmihalyi). Hence, measurement and analysis of intrinsic motivation in context has to be an important part of any computational tool for creativity analysis. The means to measure intrinsic motivation may not be limited to cognitive measurements. Wearable computing gives us means to find behavioral correlates that may be indicative of states of ‘flow’ or high intrinsic motivation.

### **Assessment of Creativity**

For the measurement of creativity, several divergent thinking tests have been designed that test for fluency or rate of ideation in individuals. Some early tests proposed to test creativity were Guilford’s Structure of Intellect (SOI) divergent production tests (Guilford, 1956), and Torrance’s Tests of Creative Thinking (TTCT) (Torrance, 1974). The SOI battery of tests have factors that represent several types of fluency (number of ideas), flexibility (variety of perspectives

represented in the ideas), originality (statistical infrequency), and elaboration (explanation of ideas beyond what is strictly demanded).

These tests for assessment of creativity differ on four scales (Sternberg, 2007): (1) Time: timed or untimed (2) Mode of instruction: game like or test like (3) Unit of analysis: individual level, or group level, or organizational level (4) Instruction type: specific instructions such as “be creative” or non-specific instructions. These four scales have been found to have different influence on the final result. In addition, these tests are susceptible to training effects where long term exposure to the tools biases users and affects the outcome as well as intervention effects where knowledge of the tools being used biases users and affects the results. To avoid these effects, some researchers have suggested alternative methods to measure creativity in longitudinal studies. One proposed alternative to normal frequency tabulation of creativity measures is using summative scores, uncommon scores, weighted fluency scores, and collective scores. These limit the statistical biases in the data. However, there is also the issue of confluence where one factor such as fluency may affect flexibility.

It is generally recognized that the above defined parametric approaches may measure only one aspect of creativity and can work only in controlled laboratory conditions. In an alternative approach, since the bedrock of creativity is the end product, several efforts have started to focus on the creative quality of the final product. These tests range from simple rating scale such as creative product semantic scale (Besemer & O’Quin, 1993) to a more complex consensual

assessment technique (CAT) (T. Amabile, 1996). Typically researchers provide the judges or raters with rating categories. For example, Csikszentmihalyi and Getzels (M. Csikszentmihalyi & Getzels, 1971) asked art critics and artists to rate drawings by art students on the basis of craftsmanship, originality, and aesthetic value. These guided ratings are motivated by creativity models such as componential model of creativity proposed by Amabile (T. Amabile, 1996).

Overall, most of these tests require that users either find new instances or applications of existing topics or sets of objects in order to demonstrate creativity. The tests assume that creativity is a quantifiable domain-independent trait of individuals. However, while creativity scores from these tests may be indicative of a person's natural tendency and inherent talent for creativity, these do not necessarily translate to creativity in a specific domain which requires a high level of expertise, idea generation, and verification (gate keeping) that is particular to a given field. Moreover, these tests do not transfer to team or small group creative activity. To address these limitations, some researchers have suggested alternative methods to evaluate team creativity. One such approach is the Consensual assessment technique (CAT) proposed by Amabile (T. Amabile 1996).

CAT can be employed to address domain specific creativity and also be extended for analysis of team creativity. In CAT, researchers provide judge raters with rating categories. CAT relies on the inter-rater reliability between these expert judges to evaluate levels of creativity in processes and products. Amabile has also developed the KEYS scale based on her componential model of creativity

(T. M. Amabile et al., 1996) that measures variety of factors such as affect, rewards, motivation, and asks the participants to self report on creativity (on a Likert scale) and to explain what they did throughout the day in an open ended question format. This scale is particularly useful since it addresses individual, team, and context variables concurrently. It also has several checks and cross checks to ensure consistency and accuracy of responses.

Another research direction lies in automated analysis of creativity through sensors and data mining. In order to create computational tools that support creativity within teams, we need to understand the basic nature of group creativity and the factors that may influence creativity. Thus, there is a need to find sensor-level measures that correlate with existing measures of creativity such as that obtained from consensual assessment technique. We expect that in the future we shall be able to reliably predict creativity by computational modeling of human behavior based on raw sensor information. This is a challenging problem since quantifying complex cognitive variables such as intelligence and creativity by physiological measures requires a long process of validity checks in interdisciplinary settings. This type of research is very much in its infancy but there is some promising initial work.

A few researchers (Burlison, Picard, Perlin, & Lippincott, 2004; Kapoor, Burlison, & Picard, 2007; Kim et al., 2007; Olguin Olguin et al., 2009) have successfully employed empirical setups that make use of physiological sensing and wearable computing to understand and predict the relationships between low

level signals and high level behavioral constructs such as affect, activity and creative output. For example, methods from affective computing have been able to distinguish affective state with 81% accuracy throughout everyday activities (Kapoor et al., 2007) while machine learning tools that incorporate Human Eigen behaviors and Coupled Hidden Markov Models (CHMMs) have been shown to account for 96% of the variance of behavior of typical individuals (Eagle, 2005). This dissertation leverages the strengths of social science survey tools and wearable computing methodologies towards new findings on creativity. In the proposed approach, wearable and mobile computing tools are embedded in user's context and integrated with users' daily routine to gather data throughout creative processes which is subsequently used for computational modeling of human creativity.

### **Group Creativity**

Work on creativity has largely focused on individual creativity. However, in recent years, there has been an increased interest in studying team creativity within organizations. An important observation is that it is not very clear how individual creativity is linked to team creativity (Pirola-Merlo & Mann, 2004). Researchers have dealt with this conundrum by focusing on individual creativity alone, or on team creativity alone, or on processes of interactions between team members (Bain, Mann, & Pirola-Merlo, 2001; Pirola-Merlo & Mann, 2004; Scott & Bruce, 1994; Taggar, 2002 ).

Group creativity can be conceived as additive or disjunctive property of individual creativity (Pirola-Merlo & Mann, 2004). If it is additive then each individual member's creativity adds up to the final creative output of the team. If it is disjunctive, the most creative ideas which may come from one or more individuals are adopted by the team. Team creativity may also manifest itself as a weighted combination of individual contributions.

Lately, several researchers have pointed that context plays an important role in the intra-individual factors and how individual creativity is related to team creativity. Amabile, in her componential model of creativity, has pointed out that intra-individual factors such as organization incentive for innovation, resources made available, and external pressure can impact individual creativity (T. Amabile, 1996). Taggar (Taggar, 2002 ) found that in addition to creativity relevant skills, domain relevant knowledge, and intrinsic motivation at the individual level, there might be group related processes that are relevant to creativity. Amabile's KEYS scale (T. M. Amabile et al., 1996) tries to quantify such variables in an efficient way and is shown to be quite reliable in measuring team creativity.

Group creativity is also studied by researchers in the field of computer supported collaborative work (CSCW). McGrath defines a group "as an intact social system that carries out multiple functions, while partially nested within, and loosely coupled to, surrounding systems (e.g. an organization)" (McGrath, 1984). In the 1960s many specialized group study systems for the analysis of specific



classes of groups or group activity were proposed. However, by the late 1970s and early 1980s, research hit the limits by the type of technology that was available for that time and suffered from lack of adequate theory to support further development (Lubich, 1995). By the 1980's new technology for data collection (e.g. sophisticated video, taping systems) and for data analysis (Fourier analysis etc.) triggered a rise in group work(Lubich, 1995). In the 2000's, group work had turned to the use of sensors for feedback and the display of group behavior (DiMicco & Bender, 2007; Kim et al., 2007). The goal was to create automated sensor-driven tools that enhance group performance. These tools employ sensors in laboratory environments and focus on single modality, such as speech (Leshed, 2009), for promoting group performance . With the introduction of personal computers, several creativity support tools (CSTs) have also been developed that aim to improve group creativity. Most of the studies in CSTs center on the comparisons of an experimental group that uses the CST system versus a nominal group ( set of individuals not acting as a group) or a control group that does not use the system (Masseti, 1996). Studies tend to focus on quantifying interactions and using them as a measure of creativity and productivity. These are discussed in the next section.

### **Role of Interactions in Group Creativity**

Research has shown that network communication strength and the types of communication modalities within a team are additional behavioral factors that may impact group creativity (Kraut, Egido, & Galegher, 1988). While there is a belief that face-to-face interaction strength is central to the understanding of

social networks in relation to creativity, there is insufficient empirical evidence to indicate strong relationship between face-to-face interaction and creativity. Tie strength (weak, strong) is a function of the amount and quality of interactions, emotional intensity, and reciprocity that takes place between two individuals (Granovetter, 1973). Zhou *et al.* (Zhou, Shin, Brass, Choi, & Zhang) found that employees exhibited greater creativity when their number of weak ties was neither too low, nor too high (an intermediate level exhibited greatest level of creativity). Perry-Smith and Shalley (Perry-Smith & Shalley, 2003) showed that weak ties rather than strong ties are beneficial for creativity among research scientists. In contrast, Obstfeld (Obstfeld, 2005) showed that engineers with strong ties are more creative. These studies show a complex, inconclusive, and possibly domain specific relationship between tie strength and creativity.

Research has also investigated the nature of structure of the social network within team, that is more supportive for creativity (Ohly, Kase, & Skerlavaj, 2010). For example, Burt (Burt, 2004) claims that a network with several structural holes (many disconnected individuals) may be more creative. Burt hypothesizes that members who are closer to these structural holes are exposed to a greater diversity of perspectives which has a positive impact on creativity. On the other hand, Perry-Smith and Shalley (Perry-Smith & Shalley, 2003) claim that a dense network with all members strongly connected to each other provides an opportunity for free interchange of information and hence greater creativity.

All these studies generally agree that interaction between key members of the team will lead to increase in domain-relevant skills and creativity relevant skills. The reliance on questionnaire based self reports from the participants however is a methodological limitation of social network studies on the importance of face-to-face network in creativity. The use of wearable computing in the real world context allows us to more reliably map the network relationships between participants. Moreover, we can distinguish between collocated interactions and remote interactions and conduct a finer grain analysis of the member interactions in a network.

Past research in group work suggests that different patterns of interaction based on in time and space can have a significant impact on group performance. Pentland(Pentland, 2008) observed that the group that has greater oscillation between periods of information discovery and periods of integration has more creativity than those groups with lesser oscillation. Information discovery is marked by group members gathering information at the individual level by talking to people outside their own group and information integration occurs when team members spend time together.

Using sociometric badges this research focuses on collocated (located in the same room) real time interactions between team members. The results will disambiguate much of the debate on the relationship between interaction tie strength (generally considered to be a function of team member's emotional intensity, reciprocity, and interaction) and creativity (Perry-Smith & Shalley,

2003). Studies on team interaction have shown promise in understanding the relationship between face-to-face interaction and team performance(Olguín-Olguín, Kam, & Pentland, 2010). Moreover, research indicates that by analyzing wearable computing data, we can evaluate the patterns of movement and interaction (discovery and integration) that contribute towards creativity. Thus, with careful implementation of reality mining approaches that link sensor data recorded in the real world to the social and cognitive variables of humans, we can gain crucial insights into the relationship between human interaction and creativity.

While face-to-face interaction has been studied to some extent in relation to creativity, movement of the team members has been largely neglected as a variable that pertains to creativity. Most research conducted on the relationship between movement and creativity is in the exercise sciences where brief period of activity such as walking on the treadmill is followed by creativity assessment questionnaires (Malone, 1989; Singh-Manoux, Hillsdon, Brunner, & Marmot, 2005). These studies have established that physical activity in humans is linked to their creativity. However, research is needed to understand how individual movement in the work environment is related to the creative production.

Movement is closely linked with sharing of information such as moving to the same location to share the artifact and moving around in the office to talk to people. Movement is hence an interesting variable for creativity. We can imagine two people in a team: person X moves a lot, while person Y moves is glued to his

or her desk. Another person Z moves a lot but also has periods of non-movement in which he or she works alone. All these scenarios are interesting in their relationships to both personal and team creativity. In essence, a certain amount of movement implies creativity by indicating sharing of artifacts and convergence of knowledge as well as dispersion and dissemination of knowledge especially in closed lab settings.

### **A Note on Assumptions and Challenges in Analyzing Group Data**

While much work has been conducted in groupwork, it is important for the reader to consider that group research is a challenging task (Saddler & Judd, 2003). Some of the common problems in group research are ensuring participation and compliance, asking the right questions, measuring group variables, and designing appropriate structure of the experimental sessions. The most difficult challenge from a statistical perspective lies in analyzing data from groups (Hoyle, Georgesén, & Webster, 2001; David A. Kenny, Mannetti, Pierro, Livi, & Kashy, 2002). Data gathered from individual participants in group studies is often interdependent which limits the use of several statistical tools for analysis. The data provided by individual group members may reflect both their own unique perceptions and the elements they share with other members of their group. Separating individual and shared factors in group data is statistically challenging.

Kenny and Judd identify three sources that might produce nonindependence in groups (D. A. Kenny & Judd, 1986; David A. Kenny et al., 2002): (1) Compositional effect occurs when the sampling of the subjects is not

random and instead is influenced by personal likes or dislikes of attributes (2) Mutual influence occurs when members interact with each other directly and reciprocally such as in a small group of friends (3) Common fate occurs when members coexist in a common environment such as team members in the work environment. In a typical laboratory environment, common fate threatens the validity of the independence assumption on the collected data.

Even with the recognition of such confounding factors, the issue of non-independence is still largely ignored in group research. In fact, Hoyle et al. reported that in 1992 and 1997, only about 60% of the publications in group work acknowledged the problem of dependency in data and one third of those papers reported analysis only at the individual level. The most frequent analytic strategy used to deal with non-dependence of data was to use group as a unit of analysis. Hierarchical Linear Modeling (HLM) was at that time proposed to be a solution to analyze data from individual in groups by Kenny et al. (D. A. Kenny, Kashy, & Bolger, 1998) but it was not used in any of the reported literature. A key element of the present analysis in this dissertation was to ensure that the approach accounted for the possibility of interdependence of data collected in various experiments.

Employing techniques such as ANOVA that rest on the independence assumption can be valid in group data as long as preliminary analysis of data shows that the observations are independent. A foremost technique to show independence is correlation analysis (Hoyle et al., 2001). In this case, non-

independence is viewed as a correlation between observations and can be either negative (when the data points are dissimilar but predictably related) or positive (when they are similar and predictably related) (D. A. Kenny, Mannetti, Pierro, & Livi, 2002). In general, if intraclass correlation coefficient is effectively zero for the observed data points, it can be concluded that non-independence of data does not hold. In that case, no group-level inferences (using group as a unit for analysis) are necessary, and the analysis focuses on individual level effects. If this coefficient is nonzero, then effects at the individual level are estimated after group-level effects have been estimated (using multilevel models) (Christensen & Bedrick, 1997; Griffin & Gonzalez, 1995; Hoyle et al., 2001; D. A. Kenny & Judd, 1996; Moritz & Watson, 1998). In this dissertation, calculation of intraclass coefficients confirmed that assumption of independence of data is valid (since the coefficients were effectively zero).

## Chapter 3

### INSTRUMENTS AND METHODS FOR THE MEASUREMENT OF GROUP CREATIVITY

This chapter details the instruments and methods used for measurement of group creativity. This dissertation uses a multi-methodological approach drawing upon computer science and social science. It uses a combination of a daily online survey based on KEYS scale, previously used by Amabile et al. (T. M. Amabile et al., 1996) to measure creativity. It also uses sociometric badges from the Human Dynamic group at the MIT Media Lab (Pentland, 2007) to measure group activity.

#### **Sociometric Badges**

Sociometric badges are a type of wearable computing, such as PDA and cell phone devices, worn around the neck (See Figure 1 and 2). The badges record network data (Infra Red pings) at 17 Hz, body movements (2D accelerometer) at 50 Hz and ambient audio using embedded speaker at 8 kHz. In addition, these badges have their own power supply (charged through USB) and a storage device. Thus, sociometric badges track location and analyze elements of participant's social interaction through bi-directional infrared transceiver, accelerometer, and low-resolution microphone analysis. No personally identifiable data is recorded which ensures privacy of subjects. The raw data from the sensors needs to be analyzed to extract meaningful features that may correlate with team members' characteristics. The process of feature extraction from the raw sensor stream is described below.





*Figure 1.* Front and back of a sociometric badge.



*Figure 2.* A participant is wearing the badge around his neck.

### Calculating Average Movement Energy

Badges are equipped with triaxial accelerometers that give the value of movement in X, Y, and Z directions. Figure 3 plots raw accelerometer values of a badge when the badge was moved up and down 1 meter in the X, Y, Z direction respectively at every 1 minute. Using the standard value for gravity ( $g = 9.8 \text{ m/s}^2$ ), and initial starting values of X, Y, and Z as baseline, normalized X, Y, Z values were calculated. Figure 4 shows the plot of normalized values.

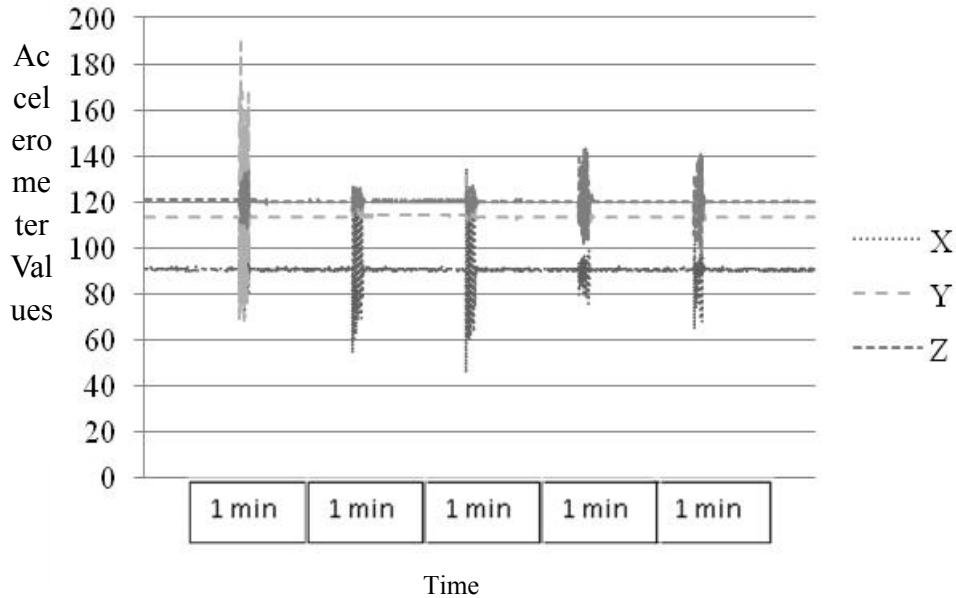


Figure 3. Raw accelerometer values of a badge when the badge was moved up and down 1 m in X, Y, Z direction respectively every 1 minute are shown.

Finally movement energy array was calculated by the following formula:

$$\text{Movement Energy} = \sqrt{(X_{\text{norm}}^2 + Y_{\text{norm}}^2 + Z_{\text{norm}}^2)}$$

where  $X_{\text{norm}}$ ,  $Y_{\text{norm}}$ , and  $Z_{\text{norm}}$  are normalized values of X, Y, Z axis.

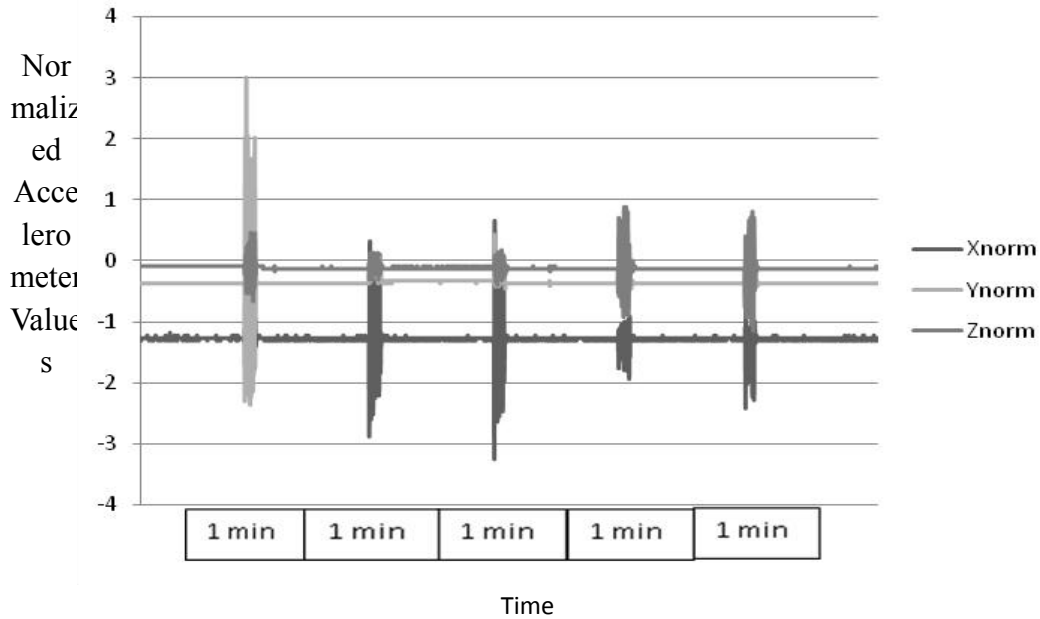


Figure 4. Xnorm, Ynorm, and Znorm, normalized values of X, Y, Z axis respectively, are plotted against time.

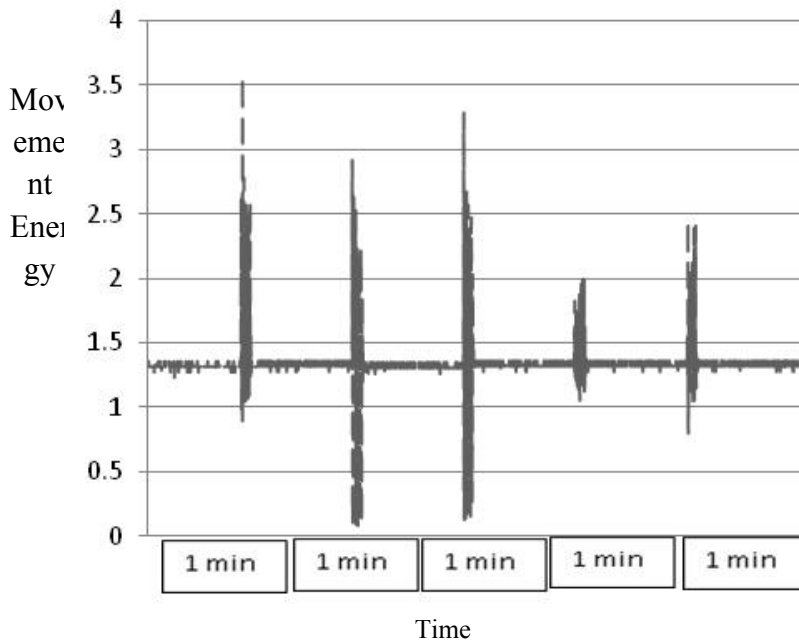


Figure 5. Movement energy values for the sample badge. The mean energy calculated for this array was 1.33 with a standard deviation of 0.17. The total number of samples in this test sample was 4432.

The movement energy array (see Figure 5) was used to calculate the mean and standard deviation of movement energy for each participant for each day.

Movement energy gives a measure of the intensity of individual movement that includes the effect of variation in signal around the three axes in the accelerometer (Olguin Olguin et al., 2009). Activity recognition based on movement energy is an extensively researched area and various papers have focused on how the signal stream from the X, Y, Z may be correctly classified into various types of physical activity such as walking, running, and sleeping (Ravi, Dandekar, Mysore, & Littman, 2005).



*Figure 6.* Participants wearing sociometric badges during a group meeting.

### **Calculating Face-To-Face Tie Strength**

Infrared signals in the sociometric badges are used to give us a measure of face-to-face interaction (Figure 6 shows participants in a group meeting wearing

sociometric badges). Badges record presence and duration of other badges when they are in direct line of each other (IR signal cone of height  $\leq 1$  meter and radius  $r \leq h \tan \Theta$  where  $\Theta = \pm 15^\circ$ ) (Olguin Olguin et al., 2009). We counted the number of pings for each badge and constructed adjacency matrix for the data. Cells in the adjacency matrix represent the number of pings recorded for each badge with all other badges. This matrix was first made symmetric with respect to the minimum number of pings recorded for each pair. Subsequently, the adjacency matrix was used to generate face-to-face tie strength for each day (Total pings/Detected Number of Badges) for each participant. The badges have been extensively validated over several studies (Basu, 2002; Choudhary, 2004; Kim et al., 2007; Olguin Olguin et al., 2009; Pentland, 2008). We now discuss tools to measure creativity in the dissertation.

### **KEYS Scale**

To obtain daily measures of creativity from the participants, we employed a version of electronic Experience Sampling Methodology (ESM) based KEYS daily questionnaire (T. M. Amabile et al., 1996) (See Appedix A). KEYS scale includes items related to creativity, affect, and external environmental factors for that particular day. It is based on the componential model of creativity proposed by Amabile (T. M. Amabile, 1983).

The KEYS survey is designed to assess the perceived stimulants and obstacles to creativity in organizational work environments. Items of KEYS scale address negative and positive aspects of the environment. It is widely recognized

as the current standard for measuring team creativity and innovation within organizational work environments (T. M. Amabile et al., 2005). KEYS defines creativity as a production of novel and useful ideas in any domain and innovation is defined as the successful implementation of creative ideas. The research team that developed KEYS appreciated that creativity by individuals and teams is a necessary but not sufficient condition for innovation in organizations. They considered team creativity to be the starting point for organizational innovation (T. M. Amabile et al., 1996).

The KEYS survey has fifteen questions two of which are open ended responses. A 7 point Likert scale (ordinal measures) (1 – ‘not at all’ and 7 – ‘extremely’) is used for each of the questions. Our first measure is self-rated creativity that is extracted from the report of team creativity. The variable assesses member reports of creativity being experienced by the team. For the open ended questions, participants were asked to 1) “In a few words, briefly describe the major work you did on the assigned project pertaining to this study today, or the major activities you engaged in that were relevant to the target project” 2) “Briefly describe ONE event from today that stands out in your mind as relevant to the target project, your feelings about this project, your work on this project, your team’s feelings about this project, or your team’s work on this project”.

KEYS requires an expert judge to rate the participants’ reports by assigning numerical value for the level of creativity (0 or 1) in addition to the self-reports through questionnaire. It has been shown to be reliable when the rating is

conducted with one or more expert judges. Expert is defined as a person knowledgeable about domain.

Table 1.

*A sample of combined narrative into events. CODE represents Event Number\_ParticipantID\_Day. Adding the layer to connective tissue was previously described as a routine task by the participant.*

CODE	EVENTS	CREATIVE (1/0)
11_P6_D4	Work on Cholecystectomy [sic] scene. Made a minor breakthrough today. A physics asset of a gall bladder model seemed to interact well. I pursued that lead with Cord and as it turned out I managed to create with his help a very nicely interacting model of the gall bladder.	1
12_P6_D4	Besides this I spent the day adding another layer to the connective tissue.	0

In this dissertation, the method described by Amabile et al. (T. M. Amabile et al., 2005) was followed to obtain expert coded creativity. The descriptions from the open ended questions were combined together to form open-ended narratives for each participant. Unique instances of completed actions were extracted from the narrative for each participant to identify individual ‘events’. The KEYS coding protocol defines creative thought as any of the following: (1) a discovery, insight, or idea; (2) the act of searching for a discovery, insight, or idea; (3) solving a problem in a non-routine way; or (4) the act of searching for a problem solution in a non-routine way. Events that had any of these were labeled 1 and events that did not have any of these were given 0. Table 1 illustrates the process through an example. In the code of the form “X\_Y\_Z”, X

stands for index number of the event, Y is the participant ID that was assigned prior to the experiment, and Z is index number of the day the event occurred.

The basic assumption of KEYS is that psychological perceptions of work environment by the team members play a vital role in their creativity. The underlying model (T. Amabile, 1993) identifies three components within the individual that have an effect on creativity, including individual's intrinsic motivation, their thinking style, and domain relevant knowledge. The KEYS scales has been validated over several studies and is reported to have high validity and reliability of creativity scores (median Cronbach alpha = 0.84, test-retest reliability = 0.87); high content validity (items measure the content they were intended to measure) (median r with KEYS scale for stimulants and obstacles = 0.46); convergent validity (scores predict a criterion measure and results correlate with other results) (median r with WES scales = 0.43); and discriminant validity (items measure hypothetical constructs or concepts). (median r with WPI scales = 0.09, KAI  $r = -0.02$ ) (T. M. Amabile et al., 1996).



## Chapter 4

### CONCEPTUAL FRAMEWORK

This chapter explains the conceptual framework that guides the experimental design and rationale of this dissertation. In past work, some creativity tasks performed in laboratory settings, implicitly embody movement and speech while some emphasize cognitive processes. There are few studies in the exercise sciences that link creativity with general movement such as aerobic exercises. However, to the best of my knowledge, no prior work exists that has studied the direct relationship between movement and creativity and the work on face to face interaction in teams has primarily been concentrated on productivity rather than creativity. This dissertation explores the relationship between individual movement and face to face interaction and creativity within a team.

This work is motivated by seminal contributions in scientific literature on creativity and activity. In his book, *Honest Signals*, Pentland talks about four categories of human signals based on their timing, energy, and variability (Pentland, 2008): Influence (extent to which one person causes other person's pattern of speaking to match their own), mimicry (reflexive copying of gestures), activity (increased activity levels such as vigorous body movements that indicate interest and excitement), and consistency (different thoughts or emotions manifest themselves in jerky movements and speech while focused thought is manifested through consistency of emphasis and timing). As indicated by research in affect (Damasio, 1994; Darwin, 1913; Kaufmann, 2003), learning (Chi, 2009 ) as well

as research on creativity and performance using sociometric badges(Olguin Olguin et al., 2009), I chose to study the relationship of activity and creativity in teams.

Research was conducted in two broad phases. First phase was exploratory and the second phase involved careful design of “in the wild” experiments that had hypotheses derived from the exploratory study. In the exploratory study, data from a group of participants was recorded with the intention of evaluating feasibility of movement and face-to-face interactions as being valid variables of interest for studying creativity. Participants were observed over four work weeks. Their movement and interactions were recorded through sociometric badges and a daily survey was administered to explore the relationship of their activity to their creative output. Analysis of this data suggested that movement and face-to-face interaction were variables of interest with respect to creative production in a research laboratory. Informed by these results, the main experiments were designed. The two main experiments confirmed the relationship between movement and face-to-face interaction among team members to creativity in a team.

In the main experiments, participants engaged in creative work are observed for two work weeks. Participants have regular work hours (9 am -5pm) and are engaged in research intensive creative work in an information technology environment. A survey based on Amabile’s KEYS scale that assesses creativity is administered.

For the purposes of this dissertation, creativity was defined as “a product or response that can be judged as creative to the extent that (a) it is novel and appropriate, useful, correct or valuable response to the task at hand, and (b) the task is heuristic rather than algorithmic” (T. M. Amabile et al., 2005). Amabile’s work represents the best accepted tool and definition of creativity. Given its extensive validation in the real world studies of creativity, it is an adequate instrument to study the feasibility and applicability of sensor data analysis to extract creativity measures.

Movement and interaction activities of the team are recorded concurrently using wearable computing tools and experimenter observation. Accelerometer and face-to-face recordings are obtained through a wearable computing tool called sociometric badges (Olguin Olguin et al., 2009). The movement data was characterized through energy as it represents the gross effort put into physical displacement of individuals. Face-to-face interaction is captured through the infrared transceiver pings which occur when the transceivers on different badges face each other. The results of the initial experiment and informal observations indicated that the signal to noise ratio in both these data streams (defined as the ratio of valid interactions to overall interactions) will be high and the data will be sufficiently reliable to evaluate proposed hypotheses.

Data collection through two different experiments enabled testing the hypotheses linking face-to-face interaction, movement, and creativity in two separate occasions. This helped in proving generalizability of the results. The

experiments presented in this thesis strongly prescribe to the view of studying creativity in context. It is for this purpose, that I do not include any explicit tests of creativity but rather study emergent creativity both through self-report and expert-coded creativity. The experiments capture both self-reported creativity and expert-coded creativity because they represent two related yet distinct views of creativity.

Selection of participants in this dissertation was carefully designed. In the initial exploratory experiment, a team was selected from the information technology research industry. The team members were driven by time dependent goals and had project management practices imbibed in their work culture. This allowed for us to study emergent creativity in environments with high level of external motivators. For the main experiments, research teams in a Level I research university were recruited. Research teams in a Level I research university are engaged in highly creative processes with the benefit of limited influence of other factors such as time, finances, etc. The primary goal of research teams in university settings is to conduct research which involves a significant component of collaborative problem solving and group creativity.

In this way, the participants in the main experiments satisfied each of the criteria of componential model of creativity(T. M. Amabile, 1983) namely: task motivation, domain relevant skills, and creativity relevant processes. Modern research environments in the universities typically involve high use of IT, high interpersonal interaction, and collocated laboratory. The environment tends to be

competitive (publish or perish). In addition, individual freedom or latitude (lesser hierarchy) is highly valued. University research laboratories operate as independent units minimizing the external context (rewards, pay) and typically place a high value on internal context (such as personal motivations). Thus, for this dissertation, research laboratories that satisfied these conditions were selected. It may also be noted that with inclusion of teams in both industry and academia, the overall experimental design allowed for rigorous testing of generalizability of our results.

Our choice of statistical tools for the experiment was designed to ensure statistical validity of the results and generalizability. As mentioned in Chapter 3, the methodology paid special attention to ensure that the assumption of independence of data held true. From an analysis perspective, the methodology employs a mean split in creativity data to categorize events as creative or non-creative. In creativity research, it is not uncommon to split the creativity scores into different levels (Tierney & Farmer, 2002). This approach enabled comparisons between creative and non-creative events to effectively structure and test the hypotheses.

A key element of the presented work lies in design, development and evaluation of a computational model for creativity. A computational model of creativity can have several applications including automatic prediction of creativity, development of creativity support tools and creating tools for assembling teams and designing the environments to maximize creativity. I

intended to use probabilistic and deterministic tools for computational modeling of creativity. By employing both these approaches, it was possible to study the underlying model of the relationship between creativity and the sensor data. Further I employ linear techniques of analysis as they represent the least common denominator in data mining approaches and success of linear techniques could open up several possibilities of developing effective models for analysis of creativity. In the following chapters, I describe in detail the experiments, results, and discussion.

## Chapter 5

### EXPLORATORY EXPERIMENT

#### **Overview**

A pilot study was conducted to explore whether there are correlations between individual activity and self-reported team creativity in a small group. It used a combination of quantitative and qualitative data that was collected for a team of individuals over an extended period of time. These individuals worked in a industry research environment that required high levels of information technology and creativity in an industry setting. Creativity was measured through an online survey that had a combination of scale-rated responses and open ended questions that allowed participants to describe their day to day experience of creativity. A multi- methodological approach was used to explore the relationship between data obtained from the sensed activity (movement and face-to-face interaction) (Pentland, 2007) and levels of creativity collected via Electronic Experience Sampling Methodology (ESM) (T. M. Amabile et al., 2005). The results of this study informed our hypotheses for subsequent experiments.

#### **Methods**

##### **Participants**

A team of five people (2 females, 3 males; mean age = 32.4 years, range= 26-38 years) participated in a five week study (total 25 working days). All participants had undergraduate degrees in engineering and two had post-graduate degrees (1 MBA and 1 MS). The team was involved in software coding and research in a leading industrial R&D laboratory in the United States. All

participants were part of a single team engaged in highly creative research and development activities.

The participants were selected because they worked in a tightly knit single location laboratory advancing IT research. The majority of work in this laboratory is conducted by the members in a highly interactive manner. No rewards were given to participants in this study. The head of this department was contacted via email and they in turn put the experimenter in contact with the team that volunteered for the study. The study was approved by the Institutional Review Board at Arizona State University, Tempe, AZ. All participation was voluntary and participants had the option to opt out at any time.

### **Materials and Procedure**

This study used sociometric badges and the KEYS daily questionnaire (See the Chapter 3 for details on instruments).

The study was conducted at a remote site with a team involved professionally in software coding projects. The experimenter shipped the badges to the remote site at the beginning of the study. Participants were required to charge the badge on their own every night by plugging them into computers via a USB cable that was provided.

All participants were informed that the investigation was on workflow issues in team work. This was largely done to avoid any bias on part of the participants towards creativity. All participants were given a unique participation



ID through which they corresponded for the duration of the study. The participants were also informed that their responses would remain anonymous and evaluated by researchers unaffiliated with their work environment. The participants were ensured that the data would not be shared with the supervisors directly and only deidentified aggregate analysis would be presented to audience.

Before the main experiment began, subjects were requested to answer an initial demographic questionnaire. During the study, each subject wore a sociometric badge. The subjects were requested to wear the badges throughout their workday (9 am to 5 pm) during the experimental period. At the end of the day, subjects were requested to answer a daily questionnaire (see Chapter 3 on Instruments). The data collection protocol occurred for 25 days and provided us with an extensive sampling of creative, non-creative episodes and the activity profiles associated with it. A reminder was sent at 4:15 pm everyday with the survey link via email to each participant. The data was downloaded only once at the end of the study when the badges were shipped back. Except for initial clarification on how badges worked and debriefing, there was no interaction between the experimenter and the participants.

### **Data Analysis and Results**

Data from 1) KEYS daily questionnaire and 2) Sociometric Badges was analyzed for this experiment with the following methodology.

## KEYS Daily Questionnaire Results

While there are 15 questions in the KEYS survey, this analysis focused on three questions that dealt with self-rated creativity, expert-coded creativity, and measures of team interaction (other variables in the KEYS survey are beyond the scope of current investigation). Out of 125 expected responses (25 days \*5 participants), 96 daily surveys were received, and the average response rate was 76.8% with a standard deviation of 23%. From the surveys, the value for self reported creativity was obtained (Likert Scale: 1 – ‘not at all’, 7 – ‘extremely’) (see Table 2). See Table 3 for the number of hours in each workday that each participant spent with the team. See Table 4 for number of people of the team each participant interacted with during each day (degree) (see Chapter 3 on instruments for more detail).

In addition to the scaled responses, the KEYS instrument and its methodology provide the opportunity for expert coding of creative and non-creative events.

Table 2.

*The summary statistics for the self-rated creativity scores for the five participants across 25 days. (PID: Participant ID)*

	MEAN	STD DEV	MIN	MAX	N
PID 1	3.95	0.21	3	4	22
PID2	4.39	0.58	3	5	21
PID3	3.13	0.92	1	4	9
PID4	1.72	0.82	1	3	22
PID5	2.52	0.99	1	5	21

For each survey response, the narratives from the two open ended questions were combined. The participants' combined narratives ranged from 462 words to 2348 words with a mean of 53 words.

Table 3.

*The summary statistics for hours spent with team during each day across 25 days*

	MEAN	STD DEV	MIN	MAX	N
PID 1	7.8	0.85	4	8	21
PID2	5.5	1.73	2	8	19
PID3	6.4	2.92	2	10	9
PID4	7.8	0.85	4	8	21
PID5	7.8	1.39	4	10	21

Table 4.

*The summary statistics for number of team members (including self) (degree) each participant met during each day across 25 days.*

	MEAN	STD DEV	MIN	MAX	N
PID 1	2	1.33	1	5	22
PID2	4	0.87	2	5	19
PID3	2	1.56	1	5	8
PID4	3	0.84	1	5	22
PID5	3	0.99	1	5	21

Table 5.

*Expert-coded creativity scores for all the participants across 25 days.*

	# Of Events (A)	# Of Events Regarded Creative (B)	Creativity Score (B/A)	N
Pid1	67	10	0.15	22
Pid2	34	11	0.32	21
Pid3	25	1	0.04	9
Pid4	36	12	0.33	22
Pid5	53	16	0.3	21

Table 5 shows the number of events for each participant and the corresponding creativity score assigned to them across 25 days.

### **Sociometric Badges Results**

The five badges were collected at the end of the 25 day period. While the mean and standard deviation for four participants was obtained over all days successfully, one of the badges failed to record any data and the remaining four failed to record face-to-face interaction data. Due to the remote nature of the study and the lack of time stamps, the exact time and duration of wearing and taking off the badges could not be determined. Table 6 shows the summary statistics for movement energy

Table 6.

*Summary statistics for movement energy for all participants across 25 days. The data for PID4 could not be recorded due to an error.*

	MEAN	STD DEV
PID1	1.32	0.1
PID2	1.46	0.16
PID3	1.3	0.18
PID4	-	-
PID5	1.23	0.31

### **Correlation Results**

Table 7 shows Pearson correlation coefficient values obtained for all major variables. The significance value was set at 0.1 as this was an exploratory study with a low N. There was a significant large correlation ( $r=0.91$ ) between self-rated creativity and movement of the participants. There was a significant

medium correlation ( $r=0.77$ ) between speech and expert-coded creativity. There was a medium significant correlation ( $r=0.88$ ) between degree (KEYS scale) and expert-coded creativity. There was a medium negative correlation ( $r=-0.82$ ) between movement and hours spent with team (KEYS scale).

Table 7.  
*Pearson Product-Moment Correlations between All Bivariate Relationships among All Major Variables.*

VARIABLES	1	2	3	4	5
<i>Creativity Measures</i>					
(1) Self-rated creativity					
(2) Expert-coded creativity	0.15				
<i>Activity Measures</i>					
(3) Hours spent with team	-0.56	-0.07			
(4) Degree	0.34	0.88*	-0.54		
(5) Movement	0.91*	0.29	-0.82*	0.6	

N= 4

\*p-value < 0.1

### Summary

We conducted a 25 day study at a remote R&D research lab. The study investigated relationship between individual activity (movement, speech, face-to-face interaction) and creativity. We found that participants' self-rated creativity was highly correlated with their daily movement energy. However, there was low correlation between expert-coded creativity and movement and expert-coded creativity and self-reported creativity. On the other hand, the number of people a team member meets has medium correlation with expert-coded creativity.

The data indicated a few strong trends. First, participants feel more creative when they move more. Second, they are generally more creative when they are meeting more people in the team and feel more connected. As a corollary, individuals when meeting their team have limited movements indicating an interest in communication and collaboration. The data indicates that an interesting relationship exists between team members' movement, network, and creativity scores and the results warranted further investigation. To gain deeper insights into this relationship, we chose to conduct our next study in a laboratory with more direct experimenter involvement. Two bivariate relationships of interest for further investigation were identified: self-rated creativity and movement, expert-coded creativity and face-to-face interaction during this study and main experiments were designed to study these two relations.

## Chapter 6

### EXPERIMENT 1

#### **Hypotheses**

This experiment builds on the pilot study described in Chapter 5 and uses similar methodologies and procedures to investigate the following two hypotheses.

**H1.** Average daily movement energy of team members during days with above average self-rated creativity is significantly greater than the average daily movement of days with below average self-rated creativity.

**H2.** Average face-to-face tie strength of team members during days with above average expert-coded creativity is significantly greater than the average face-to-face tie strength of team members of days with below average expert-coded creativity.

#### **Methods**

##### **Participants**

Seven participants engaged in creative research were observed for two work weeks (11 days) during regular work hours (9 am -5 pm). The mean age of participants was 24.7 years (range = 24–32 years), and 4 out of 7 participants were men. The sample was highly educated, 4 out of 7 participants were college graduates engaged in postgraduate work, and 3 were senior undergraduates. The study was approved by the Institutional Review Board of Arizona State University (See Appendix B for application and approval). All participants were recruited via email and signed consent form for voluntary participation prior to

the start of the study. Approval was also obtained from the laboratory head, prior to the start of the study. No rewards were provided for participation in the study.

### **Materials and Procedure**

We employed sociometric badges and daily questionnaire used in the exploratory experiment (See Chapter 3 for details on instruments). The materials and procedures were same as the pilot study (see Chapter 5) with the following modifications.

Recruited participants worked together as a team in a Research level I university in information technology rich environments. At the beginning of the experiment, the experimenter met with participants individually to provide an overview of the study and assigned participant participation identification (PID) number. This participant ID was used for collection of data for the duration of the study for both badges as well as the daily online survey. Participants were not informed of PIDs of participants other than themselves. The experimenter kept the master list of participant names, badge number, and IDs in a single file in a secure electronic folder. This file was only accessed once at the end of the study period to categorize and save all study data and subsequently destroyed.

For 11 days, the experimenter visited the laboratory each morning to ensure that the participants' badges were worn at 9 am. The experimenter observed activities throughout the day and at 5 pm requested the participants to turn the badges off. During the experiment in the event of participants leaving the research laboratory for long periods of time, Participants were asked to turn off



the badges before they left the building and turn it back on when they enter the laboratory again. The experimenter was present on site to facilitate compliance while minimizing intrusion on the working behavior of the team. At 4:15 pm every day, an electronic reminder was sent to each participant via email that had the link to the survey to complete the survey for that day before midnight. Due to a drop in survey completion rates, on two occasions the experimenter reminded the group to complete the surveys. To ensure reliability of data and its correspondence for the day, the experimenter downloaded the data from the badges every evening and recharged the badges for the next day.

### **Data Analysis and Results**

The methodology analyzed the 1) KEYS daily questionnaire and 2) sociometric badge data.

#### **KEYS Daily Questionnaire Results**

Out of total 77 (11 days \*7 people) daily online surveys, the number of surveys filled were 58. The mean response rate was 75% with a standard deviation of 19%. From the survey, the value of self-rated creativity was calculated. Table 8 shows the summary statistics for self-rated creativity for the seven participants.

Expert-coded creativity scores were obtained by analyzing the narratives (see Chapter 3 for the description of the methodology) are reported in Table 9. Participants' combined narratives ranged from 63 words to 516 words with a mean of 290 words for each participant.

Table 8.

*The summary statistics for self-rated creativity for all participants over 11 days.*

	MEAN	STD DEV	MIN	MAX	N
PID1	3.4	1.75	1	7	7
PID2	4.38	0.41	4	6	8
PID3	4.9	0.99	3	7	4
PID4	4.04	1.59	1	7	9
PID5	6.44	0.48	6	7	11
PID6	5.6	0	6	6	9
PID7	4.2	0	4	4	10

Table 9.

*The summary statistics for expert-coded creativity Scores across 11 days.*

	MEAN	STD DEV	MIN	MAX	N
PID1	0.21	0.33	0	1	7
PID2	0.32	0.46	0	1	8
PID3	0.08	0.13	0	0.38	4
PID4	0.23	0.41	0	1	9
PID5	0.24	0.42	0	1	11
PID6	0.09	0.3	0	1	9
PID7	0.41	0.49	0	1	10

Table 10.

*The summary statistics for movement energy for seven participants across 11 days.*

	MEAN	STD DEV	MIN	MAX	N
PID1	1.26	0.01	1.25	1.27	4
PID2	1.29	0.03	1.22	1.32	10
PID3	1.35	0.04	1.3	1.38	9
PID4	1.33	0.03	1.31	1.35	9
PID5	1.35	0.04	1.3	1.4	10
PID6	1.26	0.02	1.24	1.27	6
PID7	1.27	0.02	1.24	1.32	10

### **Sociometric Badge Results**

Accelerometer data from the badge of each participant was downloaded every day. For each day, participants' movement energies were calculated. Table 10 shows summary statistics for movement across all days. The badges record

face-to-face interaction recorded by the infrared IDs of participants at distances of up to approximately 10 meters. The adjacency matrix thus obtained was made symmetric with respect to the lowest number of signals (or pings) that were recorded. The average number of pings was calculated for each participant for each day. Table 11 shows the adjacency matrix for all participants.

Table 11.

*Adjacency matrix for infrared pings (face-to-face interaction) for seven Participants across 11 days. For analysis, this was made symmetric by using the minimum value in transpose pairs.*

	PID1	PID2	PID3	PID4	PID5	PID6	PID7
PID1	0	203	5	24	8	13	5
PID2	109	0	72	24	66	25	383
PID3	8	77	0	185	18	23	112
PID4	14	222	22	0	1	0	14
PID5	13	145	10	0	0	76	118
PID6	20	73	22	4	31	0	1
PID7	9	229	94	9	114	3	0

## Experimental Results

The following four variables: (1) self-rated creativity (2) expert-coded creativity (3) movement energy (4) face-to-face tie strength were included for the analysis. The creativity data was mean split in two ways based on 1) self-rated creativity and 2) expert-coded creativity. K-Means clustering showed that there the ratio of inter-cluster distance to intra-cluster distance was high ( $R=0.94$ ) which validated the choice of mean split. For each of these two measures of creativity, the days that had values for creativity higher than the mean were labeled creative while those days that were at or below the mean value were

classified as non-creative. A paired-sample t-test for conducted for each of the hypotheses. The p value of less than 0.05 was accepted as statistically significant.

**H1 Result.** A paired-samples t-test was conducted to test H1. This t-test [ $t(36) = 3.132, p < 0.005$ ] confirmed, the hypothesis that average daily movement energy during days with above average creativity ( $M = 1.31, SD = 0.04$ ) is significantly greater than the average daily movement of days with below average creativity ( $M = 1.29, SD = 0.03$ ). The eta squared statistic (0.21) indicated a large effect size.

**H2 Result.** A paired-samples t-test was conducted to test H2. The t test [ $t(21) = 1.05, p > 0.1$ ] showed no significant difference between average face-to-face tie strength of team members during days with above average expert-coded creativity ( $M = 9.4, SD = 10$ ) and the average face-to-face tie strength of team members ( $M = 6.3, SD = 7$ ) for days with below average expert-coded creativity

### **Correlation Results**

There was a significant correlation between face-to-face interaction and both self-rated creativity and expert-coded creativity. A significant correlation was also found between movement and self-rated creativity (see Table 12).

### **Summary**

Our results show that H1 was confirmed that average movement for creative days is significantly higher than for non-creative days. However, our data failed to confirm H2, that face-to-face interaction for creative days is not significantly higher than that of non-creative days. We found that face-to-face interaction was

highly correlated with expert-coded creativity and movement was highly correlated with self-rated creativity.

Table 12.  
*Pearson Product-Moment Correlations between All Bivariate Relationships among All Major Variables.*

VARIABLES	1	2	3	4
<i>Creativity Measures</i>				
(1) Self-rated creativity				
(2) Expert-coded creativity	0.24			
<i>Activity Measures</i>				
(3) Movement	0.07	0.66*		
(4) Face-to-face tie strength	0.45**	0.45**	0.36	

N= 76

\*. Correlation is significant at the 0.01 level (2-tailed).

\*\* . Correlation is significant at the 0.1 level (2-tailed).

## Chapter 7

### EXPERIMENT 2

#### **Hypotheses**

This experiment supplements and extends results from Experiment 1 using the same methodologies and procedures to answer the following two hypotheses:

**H1.** Average daily movement energy of team members during days with above average self-rated creativity is significantly greater than the average daily movement of days with below average self-rated creativity.

**H2.** Average face-to-face interaction tie strength of team members during days with above average expert-coded creativity is significantly greater than the average face-to-face tie strength of team members of days with below average expert-coded creativity.

#### **Methods**

##### **Participants**

Seven participants engaged in creative research were observed for two work weeks (15 days) during regular work hours (10 am -5 pm). They engaged in research intensive creative work in an information technology (IT) rich environment. The mean age of participants was 27.4 years (range = 23–32 years) and 6 out of 7 participants were men. Our sample was highly educated, 4 out of 7 participants were college graduates engaged in postgraduate work, and 3 were senior undergraduates. The study was approved by the Institutional Review Board of Arizona State University (See Appendix for application and approval). All

participants were recruited via email and signed consent forms for voluntary participation prior to the start of the study. Approval was also obtained from the laboratory head prior to the start of the study and no rewards were provided for participation in the study.

### **Materials and Procedure**

In this study, I employed the sociometric badges and the KEYS daily questionnaire previously employed in the exploratory experiment and experiment 1 (See Chapter 3 for details of the instruments). The materials and procedures were same as Experiment 1 with the following modifications; however, in order to ensure a stronger understanding of face-to-face interaction and its relationship to creativity I included daily cell phone based reports in the following manner.

During each workday, participants were requested to self-report any interactions with other team members for each hour from 10 am to 5 pm. The self-report included whether or not the member was meeting with one or more other group members and a label for the episode namely, creative or non-creative. A SMS data matrix (see Table 13) was presented on the wall of the laboratory as a reminder of the codes for reports. At the end of each hour (starting at 11 am and stopping at 5 pm), the experimenter sent a SMS reminder to the participants cell phones stating “For the last hour, you were Creative 1 or Non-creative 2 and Meeting 1 or not meeting 2 (respond 1 1 if creative and meeting and so on)” to each participant. On site qualitative observations by an expert coder were used to supplement these self-reports. Qualitative observations included descriptions of

time, people involved, description of actions, and whether movement or meetings were occurring.

Table 13.

*Code matrix for SMS hourly reports. Participants reported a combination of row 1 (creative, procedural) and row 2 (meeting, not meeting).*

Creative	Non-creative
1	2
Meeting	Not meeting
1	2

The data collection protocol occurred for 15 days and provided us with an extensive sampling of creative and non-creative events and activity profiles associated with them. Data was downloaded each day for the duration of the study.

### **Data Analysis and Results**

Data from 1) KEYS daily questionnaire, 2) Sociometric Badges, and 3) SMS reports was analyzed for this experiment.

#### **KEYS Daily Questionnaire Results**

Out of a total of 105 (15\*7) daily online surveys, number of surveys filled were 76. Table 14 shows descriptive statistics of self-rated creativity for the participants. The open-ended narratives were coded to obtain scores for expert-coded creativity for all participants for each of the 15 days. The Participants' combined narratives ranged from 293 words to 1663 words with a mean of 973 words. Table 15 shows summary statistics for each participant across 15 days.



Table 14.

*The summary statistics for self-rated creativity for all participants across 15 days.*

	MEAN	STD DEV	MIN	MAX	N
PID1	3.47	0.49	3	4	7
PID2	5.95	1.07	3	7	12
PID3	5.71	1.35	1	7	13
PID4	5.08	0.72	3	6	7
PID5	6.07	0.43	6	7	7
PID6	7	0	7	7	15
PID7	4.85	1.9	1	7	15

Table 15.

*The summary statistics for expert-coded creativity for participants over 15 days.*

	MEAN	STD DEV	MIN	MAX	N
PID1	0.14	0.22	0	0.5	7
PID2	0.35	0.36	0	1	12
PID3	0.69	0.36	0	1	14
PID4	0.02	0.06	0	0.25	9
PID5	0.3	0.41	0	1	8
PID6	0.3	0.46	0	1	5
PID7	0.18	0.29	0	1	15

### **Sociometric Badge Results**

Accelerometer data from the badge of each participant was downloaded every day. By using the same formula used in our previous studies, we calculated a movement energy array that was later used to give us mean and standard deviation of movement energy for each day. Table 16 shows the descriptive statistics for movement for all participants.

The badges record infrared IDs of participants that approximately 10 meters face-to-face from each-other. The average face-to-face tie strength was calculated for each participant across 15 days. Table 17 presents the original adjacency matrix across 15 days. Table 18 presents the value of face-to-face tie strengths calculated from the adjacency matrix for each day.

Table 16.

*The summary statistics for movement energy for all participants across 15 days.*

	MEAN	ST DEV	MIN	MAX	N
PID1	1.19	0.08	1.04	1.38	10
PID2	1.33	0.06	1.22	1.45	11
PID3	1.38	0.09	1.17	1.46	10
PID4	1.37	0.01	1.35	1.4	7
PID5	1.42	0.01	1.41	1.44	7
PID6	1.36	0.01	1.35	1.38	7
PID7	1.32	0.05	1.24	1.38	10

Table 17.

*Adjacency matrix of infrared pings (face-to-face interaction) for participants across 15 days.*

	PID1	PID2	PID3	PID4	PID5	PID6	PID7
PID1	0	0	12	0	65	33	22
PID2	14	0	101	3	4	0	26
PID3	12	143	0	0	64	15	88
PID4	0	3	15	0	0	61	19
PID5	11	1	38	0	0	18	166
PID6	32	0	16	3	1	0	17
PID7	39	35	161	34	118	8	0

## Experimental Results

We obtained the following four variables for each participant for 15 days:

- (1) self-rated creativity (2) expert-coded creativity (3) movement energy (4) average face-to-face tie strength. The data was mean split in two ways based on

Table 18.

*The summary statistics of the participants for face-to-face average tie strength across 15 days.*

	MEAN	STD DEV	MIN	MAX	N
PID1	1.23	1.65	0	4.71	10
PID2	1.25	2.91	0	10.57	11
PID3	2.97	4.8	0	16.14	10
PID4	0.41	0.9	0	3	7
PID5	2.11	3.03	0	8.71	7
PID6	0.69	0.95	0	2.88	7
PID7	3.75	4.46	0	15.43	10

1) self-rated creativity and 2) expert-coded creativity. For each of these two measures of creativity, the days that had values for creativity higher than the mean were labeled creative while those days that were at or below the mean value were classified as non-creative. A paired-sample t-test was conducted to analyze the hypotheses.

**H1 Result.** A paired-samples t test was conducted to test H1. The t test [ $t(23) = 6.49, p < 0.001$ ] confirmed that average daily movement energy during days with above average self-rated creativity ( $M = 1.37, SD = 0.07$ ) is significantly greater than the average daily movement of days with below average self-rated creativity ( $M = 1.24, SD = 0.09$ ). The eta squared statistic (0.36) indicated a large effect size.

**H2 Result.** A paired-samples t test was conducted to test H2. The t test [ $t(41) = 2.36, p < 0.01$ ] showed average face-to-face tie strength of team members during days with above average expert-coded creativity ( $M = 2.69, SD = 4.01$ ) is significantly greater than the average face-to-face tie strength of team members

for days with below average expert-coded creativity ( $M = 0.9$ ,  $SD = 2.1$ ). The eta squared statistic (0.11) indicated a large effect size.

### Correlation Results

Pearson product-moment correlations between all major variables in the study were calculated (Table 19). We found that self-rated creativity was weakly but significantly correlated with expert-coded creativity ( $r = 0.25$ ). In addition, movement and self-rated creativity were significantly correlated ( $r = 0.55$ ). Face-to-face interaction had significant correlation with both self-rated creativity ( $r = 0.20$ ) and expert-coded creativity ( $r = 0.25$ ).

Table 19.  
*Pearson Product-Moment Correlations between All Bivariate Relationships among All Major Variables*

VARIABLES	1	2	3	4
<i>Creativity Measures</i>				
(1) Self-rated creativity				
(2) Expert-coded creativity	.25**			
<i>Activity Measures</i>				
(3) Movement	.55**	0.15		
(4) Face-to-face tie strength	.20*	.25*	0.157	

N= 105

\*. Correlation is significant at the 0.05 level (2-tailed).

\*\*. Correlation is significant at the 0.01 level (2-tailed).

### SMS Results

A total 99 hours of data was collected for 1 hour intervals of self-reported daily activity indicating whether meetings or non-meetings were occurring and

whether or not these hours were creative. We summed across all days for four variables: (1) Creative and Meeting (2) Creative and Not meeting (3) Non-creative and Meeting and (4) Non-creative and Not meeting. Table 20 shows the summary of SMS reports across all days. We found that people reported to be creative while they were meeting (165 hours) more than twice than when they reported to be not creative while meeting (71). The correlation between self-rated creativity and creative and meeting reports was found to be significant ( $r = 0.82$ ,  $p < 0.01$ ), and there was significant negative correlation between reports of non-creative and non-meeting and self-rated creativity ( $r = -0.58$ ,  $p < 0.05$ ).

Table 20.

*The summary statistics for sms based self-reports across 15 days.*

	Mean	Std Dev	N	Sum
Creative and Meeting	11.00	5.20	15	165
Non-creative and Meeting	4.73	3.43	15	71
Creative and Non-meeting	8.67	3.70	15	130
Non-creative and Non-Meeting	11.47	4.90	15	172

### Summary

A significant difference was found between team member movements for creative days and non-creative days. Creative days were also shown to have higher face-to-face interaction than the non-creative days. Participants' sms reports indicated that episodes of meeting one or more team members were twice more likely to be creative than non-creative. Moreover, across fifteen days, there was a significant correlation between meeting episodes and self-reported creativity. People were twice more likely to report non creative event when not in meeting. This indicates

that team members typically do not experience being non-creative in a meeting than otherwise. Overall, our results show that participants in a small group are likely to be more creative when they are more active in terms of both movement and face-to-face interaction.

## Chapter 8

### COMPUTATIONAL MODELING OF TEAM CREATIVITY

#### **Overview**

Experiment 1 and experiment 2 suggest an intimate relationship between activity (face-to-face interaction and movement) and creativity. From a perspective of prediction, it is feasible to develop an approach that can monitor activities within a group and classify the interactions between the teams as creative or non-creative. Such a system would allow organizations to better assess possible creative output in their teams and use this awareness to change or sustain current practices. While there is no substitute for productivity and final output analysis by managers and organizations, such a system would provide automatic formative feedback for the team on their performance and inform managers about developments during the creative process and not just after it.

Here an initial feasibility study is performed on the design, development and evaluation of an automated classification system to analyze data from wearable sensors and label events as creative or non-creative. Statistical learning techniques and pattern recognition techniques on validated features available from the sociometric badges were employed for the development of the computational models. The sensor features are described in detail in previous work with sociometric badges (Olguin Olguin et al., 2009) and I employ a subset of the available features from the badges for the analysis.

## **Background**

In past work, Olguin-Olguin et al. (Olguin Olguin et al., 2009) have developed computational techniques for studying the relation between activity measured through sociometric badges and several variables like performance in healthcare environment and studying productivity in IT domains (Wu, Waber, Aral, Brynjolfsson, & Pentland, 2008). These techniques employ signal processing techniques to extract relevant features from the data stream that correlate with social signals and measures of performance. Pentland employed eigenvector representation to study the variance of behavior of individuals (Pentland, 2007). The work showed that there was limited amount of behavior variance across days for individuals implying high predictability. In another line of analysis, Pentland employed coupled Hidden Markov Models to study the relation between features from sociometric badges and social factors such as affiliations and friendship between participants. In these works, the objective of the investigations was to validate the features extracted from the tags. Features included accelerometer signal magnitude and number of pings representing duration of face-to-face interactions (Olguin Olguin et al., 2009). These approaches informed the design of the three approaches used for computational model in this dissertation.

The first approach that was employed was standard linear regression. Linear regression employs linear models to study relationship between activity - network profiles and the creativity class. It allowed testing of a basic statistical approach for classification. The general linear regression model is given by



$$Y_i = \alpha_0 + \alpha_1 X_{i1} + \alpha_2 X_{i2} + \dots + \alpha_{p-1} X_{i(p-1)} + \dots + \varepsilon_i, \quad i = 1, 2, \dots, n. \quad (1)$$

In matrix terms this becomes

$$Y = X\alpha + \varepsilon \quad (2)$$

where  $Y_i = \alpha_0 + \alpha_1 X_{i1} + \alpha_2 X_{i2} + \dots + \alpha_{p-1} X_{i(p-1)} + \dots + \varepsilon_i$ ,  $Y$  is the vector of  $n$  responses  $Y_1, Y_2, \dots, Y_n$  and  $X$  is an  $n \times p$  matrix.  $\alpha$  is the  $p \times 1$  vector of parameters  $\alpha_0, \alpha_1, \dots, \alpha_{p-1}$ .  $\varepsilon$  is an  $n \times 1$  vector of uncorrelated errors  $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p$ . The random errors  $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p$  are assumed to be independent with mean 0 and have common variance  $\sigma^2$ . They are assumed to be normally distributed.

The principle of least squares, which involves minimizing sum of squares of errors, was employed for  $\alpha$  and  $\varepsilon$  parameter estimation.

$$Q = \sum_1^n \varepsilon_i^2 = \sum [Y_i - \alpha_0 - \alpha_1 X_{i1} - \alpha_2 X_{i2} - \dots - \alpha_{p-1} X_{i(p-1)}]^2 \quad (3)$$

The  $Y$  in our case was the label for creative or non-creative class,  $X$  was the values from the sensors and least squares enabled finding the best possible values of  $\alpha$  and  $\varepsilon$  to accurately predict creativity. The training matrix was employed to estimate the parameters by minimizing least squares for creative and non-creative class labels (based on mean split of creativity data). The prediction for the test matrix was derived by the estimated model. The recognition percentage (accuracy) was calculated as the number of correctly classified data points divided by total number of data points in the testing dataset.

The second approach that was tested to predict creativity from activity was Naïve Bayesian Classifier (NBC). NBC is particularly suitable for high

dimensional data. The aim of the NBC, as with other classifiers, is to assign an object  $V$  to one of a discrete set of categories  $C_1, C_2, \dots, C_m$  based on its observable attributes  $X_1, X_2, \dots, X_n$ . In our case, there were two categories namely creative and non-creative.  $X$  represents signals from the sensors. A Naïve Bayesian classifier was trained using maximum likelihood criterion which estimates probabilities associated with the class by relative frequency from the training set. NBC calculates the probability that a vector  $I$  as extracted from the sensors belongs to each category, conditioning on the observed attributes;  $I$  is typically assigned to the category with the greatest such probability.

For testing the accuracy of a trained NBC, we want to find the probability that test vector  $I$  belongs to each category, that is,  $P(I \in C_i | X_1, X_2, \dots, X_n)$

.Applying Bayes' Theorem, this is rewritten as

$$P(I \in C_i | X_1, X_2, \dots, X_n) = \frac{P(I \in C_i)P(X_1, X_2, \dots, X_n | I \in C_i)}{P(X_1, X_2, \dots, X_n)} \quad (4)$$

Under the mutual conditional independence assumption of NBC, the equation can be rewritten as

$$P(I \in C_i | X_1, X_2, \dots, X_n) = \frac{P(I \in C_i)P(X_1, X_2, \dots, X_n | I \in C_i)}{P(X_1, X_2, \dots, X_n)} \quad (5)$$

for each category  $C_i$ . Since the denominator is constant for all categories, we need to only calculate the numerator for each category  $i$ , choosing

$$i^* \in \arg \max P(I \in C_i) \prod_{j=1}^n P(X_j | I \in C_i)$$

and assigning I to category  $C_{i^*}$ . NBC is a stochastic approach and represents an important element of the investigations.

As a final approach, a combination of principal component analysis (PCA) for dimensionality reduction and linear discriminant analysis (LDA) for classification was selected. The original dimensionality of the obtained data was high which can significantly impact accuracy of the classification algorithms (except NBC described above). In order to address this issue, principal component analysis (PCA) was employed for dimensionality reduction. PCA is a multivariate procedure which rotates the data such that maximum variability is projected onto the new axis. Essentially, a set of correlated variables are transformed into a set of uncorrelated variables which are ordered by reducing variability. This is also the basis of dimensionality reduction, as the technique identifies underlying principal components of the data.

Let the training set of vectors be  $\Gamma_1, \Gamma_2, \Gamma_3, \dots, \Gamma_M$ , and the average vector of the set is defined by  $\Psi = \frac{1}{M} \sum_{n=1}^M \Gamma_n$ . Each vector differs from the average by the vector  $\Phi_n = \Gamma_n - \Psi$ . This set of vectors is subjected to principal component analysis, which seeks a set of M orthonormal vectors,  $\mu_n$ , that best describe the distribution of the data. The kth vector,  $\mu_k$  is chosen such that

$$\lambda_k = \frac{1}{M} \sum_{n=1}^M (\mu_k^T \Phi_n)^2$$

is maximum, subject to

$$\mu_l^T \mu_k = \begin{cases} 1, & l = k \\ 0, & \text{otherwise} \end{cases}$$

The vectors and scalars are the eigenvectors and eigenvalues, respectively, of the covariance matrix

$$C = \frac{1}{M} \sum_{n=1}^M \Phi_n \Phi_n^T = AA^T$$

where the matrix  $A = [\Phi_1 \Phi_2 \dots \Phi_M]$ .

The PCA helps reduce the dimensionality of the data and the LDA works as a classifier to maximize inter class distance in the new space between the creative and non-creative classes. LDA aims to find a hyper-plane that with most accuracy can separate the underlying classes. So in the reduced dimensional space, LDA was applied on the training data to define the hyper-plane and then the testing data was passed through an algorithm that evaluated whether the testing data point was creative or non-creative. This kind of approach that combines PCA with LDA has been done before in face recognition (Li, Zhao, & Zhang, 2009). This combined approach is a sophisticated deterministic approach to computational modeling of creativity.

In each of the algorithms, maximum likelihood estimation (MLE) was used as the training approach. MLE is used to take the training data and estimate the parameters of the model that may have generated the data. In the case of linear

regression, MLE tries to estimate the coefficients of regression. In case of NBC, it tries to estimate to conditional probabilities. In LDA, it is used to estimate the equation of the hyper-plane.

Each of these three approaches described above and their underlying theory are presented in Duda, Hart and Stork (Duda, Hart , & Stork, 2000). These three methods enable development of the computational model using stochastic and deterministic approaches. Matlab 2009® was employed to develop these algorithms. The inbuilt implementation of these algorithms was used in the analysis (*glmfit* for linear regression, *NaiveBayes.fit* and *predict* for Naïve Bayesian Classifier and *classify* function for LDA).

### **Procedure**

Data from experiment 1 and experiment 2 provided day to day team member's activity and overall creativity scores. The data sets were combined and the days were divided into two classes: creative and non-creative based on the mean split of reported creativity measures. The movement data was divided based on self-rated creativity while the face-to-face interaction (or network pings) data was divided based on expert-coded creativity. The corresponding measures were chosen to classify the data based on the results from experiment 1 and experiment 2. Overall 182 hours of data per subject (participant n=7, for 26 days) totaling 1274 hours of data was collected. The activity as measured through accelerometer (X, Y, and Z) and network pings from IR were considered for analysis.

For face to face quantification, the average IR ping information for the day for each participant was considered for the computational model. As each experiment had 7 participants, we had a 7x7 matrix of face-to-face network pings as sensed by the IR sensor for each day. For every day, I calculated the frequency of pings for every pair of participants which could be understood as network edge strength in the team's network. In the team network, participants are the node and the edges represent face-to-face interactions. I had 26 days worth of network data, out of which 14 were labeled creative and 12 were labeled as non-creative according to expert-coded creativity. The 7x7 matrix of IR ping frequency for each day was linearized into a 49x1 vector representing pings per day for all possible person-person interactions. The creativity class (creative or non-creative) for each vector was known. This matrix was employed to train and test pattern recognition algorithms to assess expert-coded creativity as this was the measure that was present in experiment 1 and experiment 2.

For movement analysis, the accelerometer readings were sampled at 50,000 readings per day with 3 measures per reading (X,Y,Z), to define a representative sample of activity profile for each day. The day-activity matrix was assembled by linearizing the accelerometer activity into a vector and then assembling the individual vectors into a matrix. For each vector, a class of creativity (creative or non-creative) was known. This matrix was employed to train and test pattern recognition algorithms to assess creativity.

The investigation tested three different approaches of pattern recognition described above. For each approach, an 80/20 train/test paradigm was employed. I trained the algorithms for movement data and network ping (face-to-face interaction) data individually as they provided related but distinct information and related with different measures of creativity. In the analysis of face-to-face interactions, the core idea was to classify the entire day as being creative or non-creative for the whole team. This computational engine was tuned to gestalt creativity classification for an entire day and it hence provided complementary information to movement data based classifier that was giving us per day per person rating. Network ping based classifier was geared towards assessing team's everyday creativity.

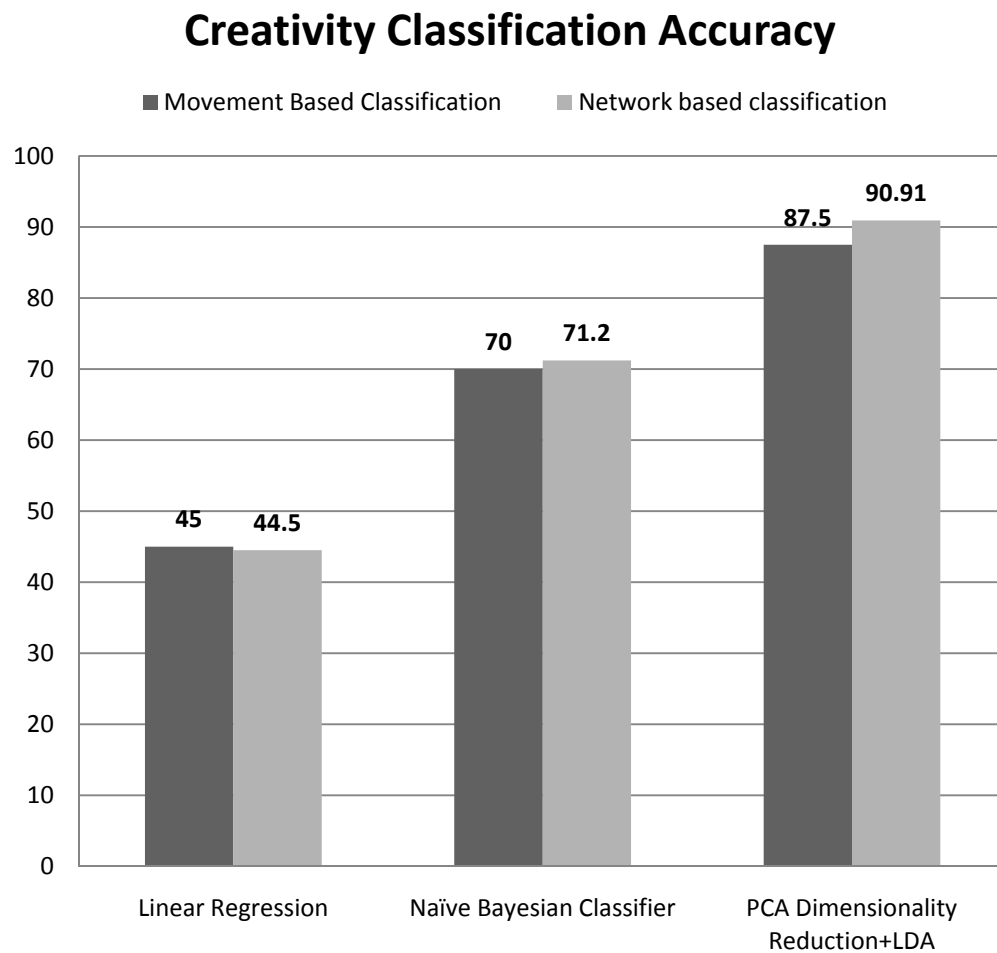
## **Results**

The first technique used on movement based classification was linear regression. Linear regression aims to define a linear relationship between the features which in this case were readings from the accelerometer and creativity classification. The second technique used was naïve Bayesian classification (NBC) which is stochastic or a probabilistic classifier based on the Bayes theorem.

In the third technique, I chose to apply PCA for dimensionality reduction and LDA for classification as a means of achieving high accuracy and fast computation results. By noting the energy of the eigenvalues it was seen that 7 dimensions were sufficient to cover 95% of variance with the movement data.

Hence, using PCA I reduced the dimensionality of the data from 150000 to 7. After PCA, I employed linear discriminant analysis as the classification technique. In the case of face-to-face interaction strength, I found that 3 dimensions were sufficient to represent 95% of variance in PCA and hence I reduced dimensionality to 3 and performed LDA for classification.

The results of the experiment with movement data and network data are shown in Figure 7.



*Figure 7.* Classification Accuracy of Creativity Recognition Models



For movement data, linear regression showed the lowest classification accuracy of 45.2%. The fit was not high or significant for movement where  $r = 0.32$  and  $p < 0.6$  or for face-to-face interaction where  $r = 0.43$  and  $p < 0.3$ . Naïve Bayesian Classifier showed an accuracy of 70.2%. The Bayesian fit actually performed significantly better than linear regression achieving accuracies of about 70% for both movement and face-to-face interaction data. The combined approach of principal component analysis and linear discriminant analysis showed an accuracy of 87.5% for per day per person data as measured through the movement stream and 90.91% creativity for face-to-face interaction.

Additional experiments on using reduced dimensionality data for linear regression and the Naïve Bayesian Classifier showed slight improvements achieving 47.1% and 71% classification accuracy. This suggests the superiority of the PCA/LDA approach in obtaining accurate classification. The results for face-to-face interaction data were analogous, with the PCA/LDA combination achieving the highest recognition accuracy of 90.9%, NBC achieving 71.2% and linear regression achieving an accuracy of 44.5%.

### **Discussion**

While the results are on a limited data set and require further validation, it is encouraging to note that computational engine can be designed to ascertain creativity from sensor data. I used linear techniques such as PCA, LDA for my analysis which yielded close to 92% accuracy. While we cannot imply causality to this result, the fact that linear approaches give encouraging results opens up

several possibilities for analysis of creativity in an automated fashion. The two approaches NBC and PCA-LDA combination both have unique advantages and requirements. NBC can be very successful in developing long term trends and patterns and can be employed in a formative fashion. The PCA-LDA combination can actually give the highest accuracy as it removes noise from the original data. Noise may have contributed to low accuracy in the results of linear regression.

The results suggest the feasibility of developing an automated approach to classify creative days from non-creative days by monitoring activities through sociometric badges and also personal creativity. We trained and tested on data gathered at two different occasions which suggests robustness and generalizability of the approach. As mentioned before, such an approach could have a significant impact on how teams and organizations gauge the output of a day and facilitate conditions and interventions that improve their creative output.

The results also suggest how computational models can augment the information base of managers in making creativity support tools. While currently there is no substitute for observations and ethnographic approaches, computational models can inform better quality of ethnographic analysis. This is a key finding of this investigation and will benefit from further study in the future. This feasibility study also suggests that there is scope for development of more sophisticated pattern recognition approaches to identify the creative events from non-creative events.

It must be noted that I used 80-20 analysis for the modeling. I felt that such a limited data set, it will not be useful to conduct a more extensive testing. Collected data gives an indication of general trend of the relationship. A more plausible analysis would be to model creativity based on teams. For this, data on several teams must be collected in identical conditions and then some teams should be used to train the data and others to test the data. This would be an interesting enterprise. However, as there has been no prior attempt at modeling creativity based on wearable computing measures, this dissertation paves the way for such future work.

### **Summary**

Computational modeling of team creativity has several benefits. (1) It allows automated evaluation and prediction of creativity. (2) It paves the way for software and programs that support creativity. (3) It allows development of guidelines and procedures towards creativity in teams and within organizations. (4) It enhances our theoretical understanding of creativity and its relationship to team member activity. In this chapter, I presented results of computational modeling that I performed on sensor data from experiment 1 and experiment 2. Three different algorithms (linear regression, NBC, and LDA and PCA) were employed to conduct automated analysis of creativity with two approaches achieving high accuracy. In summary, the modeling results indicate a definite possibility measuring creativity through wearable sensors and assessment of everyday creativity using a computational model.

## Chapter 9

### DISCUSSION

An exploratory study and two main experiments were conducted with three teams to study the relationship between team member's activity (face-to-face interaction and movement) and team creativity. For measurement of creativity, a social science instrument KEYS (T. M. Amabile et al., 1996) was employed. Sociometric badges (Pentland, 2007) was used concurrently to obtain signal data of participants' movement and face-to-face interaction. The exploratory study indicated that movement and face-to-face interaction between the team members might be significant indicators of their creativity. Subsequent studies confirmed this hypothesis and a computational model was developed that allowed for automated analysis of creativity. In this chapter, I shall critically summarize and analyze the results of the experiments.

An individuals' activity was defined in the experiments as daily movement energy and face-to-face interaction. Creativity is defined as production of novel and useful ideas in any domain and innovation is defined as the successful implementation of creative ideas (T. M. Amabile et al., 2005). For analysis, the data was first aggregated from each participant across all days. Then data from movement energy and face-to-face tie strength was mean split twice once on the basis of self-rated creativity and once on the basis of expert-coded creativity resulting into four groups (two creative and two-non-creative). I found that there

is a significant relationship between (1) individual movement and self-rated creativity and (2) face-to-face interaction and expert-coded creativity.

Specifically, I found that daily movement energy for creative days was significantly higher than the movement energy of the non-creative days for team members. In terms of face-to-face interaction, in experiment 1, while I did not find a significant difference between face-to-face interaction for creative and noncreative days classified on the basis of expert-coded creativity, the trend in significance encouraged me to explore the relationship further in experiment 2. In the second experiment, a well accepted sms based ESM was implemented to gather participants report on their ongoing behavior (Weisner, 2001). These hourly reports were collected at the end of every hour in the workday through an experimenter reminder.

I found that participants reported the highest number of both creative and meeting and noncreative and not-meeting episodes. The third highest number was creative and not-meeting. The least reported variable was not creative and meeting. This suggests that participants were generally more creative when they were meeting and generally more non-creative when they were not meeting. However, an important component of overall team creativity is a combination of team and individual creativity. I found that the reports of being creative and not-meeting were on the same days they had reported to be creative and meeting. Therefore, teams were far more creative on days in which the members meet. Team members also report to be personally more creative after active interactions

with other team members. In experiment 2, I found that face-to-face tie strength was significantly greater in the creative days than that of non-creative days.

The results show a strong correlation between movement and self-rated creativity. Prior studies have found that exercise or a physical activity of some kind enhances cognitive performance (Singh-Manoux et al., 2005) and physical activity is correlated with creativity (Malone, 1989). While the results of these prior studies were based on questionnaire data implemented on the middle aged or elderly populations, the presented research is the first effort of its kind to employ a multi-methodological approach that confirms the relationship between objective movement data with creativity.

There were two other data streams that were interesting but were not chosen. First, badges also record speech (Olguin Olguin et al., 2009). Disambiguating speech that is purposefully employed in a team versus that from outside the context of the team was not feasible in the groups that were studied. The laboratories had highly interactive environments with members from participating teams and their frequent interactions with members of a larger group such as that of the university at large. In addition, chatting, phones, and music, etc contributed to the recorded speech and might have further complicated any evaluation of the hypotheses. In other words, the signal to noise ratio in speech was very low and hence limited meaningful analysis.

In the KEYS scale, there are two variables namely individual creativity and team creativity. Interestingly, there was 94% correlation between reported

scores of team creativity and individual creativity. This might be because individual participants had no prior definition of creativity or basis of differentiating between the two variables. This is a rich and active area of research. This does raise the question of what exactly the two variables personal creativity and team creativity represent in the KEYS scale. The results point out that how participants feel about their own creativity (self-reported personal creativity) may be the same as how they rate their team as being creative (team creativity). It must be noted that the creativity score obtained by an expert that is based on their descriptions is not necessarily correlated with their creativity self-reports. This could be due to the fact that in essence they are measuring two different facets of creativity. However from a systems perspective, putting these two measures in close coherence may have strong benefits. The results indicate the need of stronger assessment tools for measuring team creativity in the wild that accounts for the need of this coherence.

An interesting aspect is that the movement is highly correlated with the self-reported scores of team creativity. On the other hand, expert-coded creativity is highly correlated with team members' face-to-face interaction. The observations strengthen existing arguments in favor of consensual assessment techniques for assessment of creativity as opposed to self-reports of creativity. Another thing that must be noted is that links have been shown between positive affect and creativity and there might be a triad of positive affect manifesting itself through increased movement. However, in the interest of showing a strong link between wearable computing data and creativity, I have considered the discussion

between other variables outside the scope of this dissertation. Link between emotions, context, and creativity is a fertile research area and in future, addition of affective computing will give greater insights into the relationship indicated in this dissertation.

Several key questions need to be answered with respect to the nature of following question: how much and how often team interactions should occur for the team to be more creative? To provide clues to some of these questions, I explored the role of degree (number of team members meeting each other) in both the experiments and found that in both cases it was not significant [ $t(36) = 1.55$ ,  $p > 0.12$ ;  $t(20) = 0.23$ ,  $p > 0.8$ ]. The means in the two cases in both the experiments were almost equivalent (Non Creative:  $M = 1.81$ ,  $SD = 1.68$ ;  $M = 1.67$ ,  $SD = 1.8$ ; Creative:  $M = 1.24$ ,  $SD = 1.38$ ;  $M = 1.52$ ,  $SD = 1.5$ ). Thus it is not the number of people a team member meets with, but rather the quality of face-to-face interaction (or the time spent with the team members) that influences creativity.

The computational modeling results show the feasibility of developing an automated system for creativity based on team members' activities. Linear regression analysis did not yield high accuracy but the Bayesian modeling and the combined PCA and LDA approach had high recognition accuracies. Bayesian approaches are very helpful in developing scalable algorithms due to their iterative nature. They also are successful in high dimensional spaces which is a dominant feature of the activity based data sensed in a continuous manner. Both



motion based and face-to-face interaction based classifiers show comparable accuracy with Bayesian approaches. This dissertation extends applicability of Bayesian approaches in classifying team creativity based on team activity.

Principal component analysis showed that 7 dimensions encompassed close to 95% variation in the underlying data from movement data and 3 dimensions encompassed 95% variation in the face-to-face interaction data. The analysis of principal dimensions and the weights of the individual units were very interesting. It was seen that the principal component gave the highest weight to an individual with highest creativity and lowest weight to an individual with lowest creativity. PCA and LDA both are linear approaches which suggest that creativity may have a linear relationship with activity in a lower dimensional space that accounts for maximal variance within the data. While this hypothesis needs to be explored in more detail, if true it suggests that several pattern recognition engines could be trained and tested for creativity analysis.

## Chapter 10

### CONCLUSION

This chapter summarizes the major findings of the dissertation. In addition, it presents the significance and implications of the conclusions drawn from the reported results. Short and long term future work is briefly discussed.

#### **Summary of Results**

Broadly speaking, the presented research had two phases. In the first phase, the effective combination of sociometric badges and creative scales was explored. This exploration was guided by review of previous work from multiple disciplines emphasizing the interdisciplinary foundations of creativity research. The goal was to derive a meaningful relationship between activity (face-to-face interaction and movement) and creativity in teams. This led me to initial indications of the relationship between team activity and team creativity. The second phase was confirmatory. In the two main experiments, the findings about the relationship between team activity and teams, in terms of the measures that were utilized, are:

- (1) The days in which the team is highly creative are also the days in which the teams' members meet more often,
- (2) On days in which team members report to be highly creative also have higher levels of movement among team members than the days they report to be non-creative.

### **Contributions and Intellectual Merit**

This dissertation contributes to the basic science of creativity and to the empirical methodologies that assess creativity. It contributes to the design of creativity support tools that are based on movement and face-to-face interactions by providing a means of continuously measuring and sensing creativity accurately and with minimal human inputs. Overall, the results of this dissertation enhance the understanding of the nature and mechanisms of team creativity. In addition, the dissertation links wearable computing data with creativity survey instruments. It implements a novel multi-methodological approach that enables empirical investigations based on coupling of sensor based analysis with creative behavior assessment in the wild.

### **Benefits and Broader Impact**

The findings from this research may benefit organizational theorists who wish to gain further insights into the nature of creativity and designers and programmers who wish to design applications that track, estimate, or predict creativity. It contributes to the design and development of creativity support tools in computer supported collaborative work (CSCW) by providing a robust automatic method to measure creativity. The findings of the research can be applied to the broad framework of sensor-behavior coupling and may impact various domains such as education, health, and innovation.

### **Future Work**

Recent advances in sensors and wearable computing tools enable objective tracking and modeling of human behavior. In the near term, I would like to

advance the findings of this dissertation to create interventions and study their impact on creativity. Future work in computational models will include development of algorithms for assessing creativity levels based on individual data streams and also developing multisensory fusion models for combining inputs from different activity domains to yield creativity measures. I will also explore nonlinear algorithms such as Manifold learning (Duda et al., 2000) for accuracy of recognition.

In future, I would like to conduct temporal analysis and assessment of team creativity at a much finer granularity. In this dissertation I did not deal with the variables of affect and creativity. This relationship would be explored in the future. The relationship between physiological and behavior measures will give us important insights into creativity as well. I would also like to investigate how CST might be implemented using movement and if there is any basis for causal relationships between the variables. More broadly, I would like to advance richer computational models and empirical frameworks that estimate and predict cognitive and social variables of humans from sensor based data and inform human centered technology design by these models across areas such as problem solving in education, medicine, and policy.

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APPENDIX A

KEYS DAILY QUESTIONNAIRE

APPENDIX B

IRB APPLICATION AND APPROVAL

PDF Export

## Studying Group Work Flow Process

### SECTION 1

\* 0001:

Enter your participant ID as assigned to you at the beginning of the study:

Please choose \*only one\* of the following:

- 1
- 2
- 3
- 4
- 5
- 6
- 7

0004:

In a few words, briefly describe the major work you did on the assigned project pertaining to this study today, or the major activities you engaged in that were relevant to the target project.

Please write your answer here:

0005:

Number of hours you spent working on the target project "today" (e.g. 1, 2.5, 7.25)

Please write your answer here:

0006:

% Percent of this time spent working with other members of your team (e.g. 33.33, 50, 85)

Please write your answer here:

0007: Number of project team members (including yourself) that you worked with "today"

Please write your answer here:

### SECTION 2

\* 0001:







Positive interactions between the team and the supervisor	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
High-level management encouragement of our team's creativity	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Fair evaluation of our project work	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Recognition and reward for creative work on the project	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Collaborative idea-flow across the organization, concerning this project	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Political problems or contention about this project within the organization	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
A conservative, low-risk attitude toward this project within the organization	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

### SECTION5

**0001:** Today, OVERALL, I felt...

Please choose the appropriate response for each item:

	not at all	slightly	somewhat	moderately	quite a bit	very much	extremely
relaxed	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
frustrated	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
happy	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
energetic	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
distracted	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
imaginative	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

### SECTION6

**\* 0001:**

Briefly describe ONE event from today that stands out in your mind as relevant to the target project, your feelings about this project, your work on this project, your team's feelings about this project, or your team's work on this project.

**\*\* Remember to specify who was involved and what happened. \*\***

**\*\* The event can be positive, negative, or neutral. \*\***

Please write your answer here:



---

**0002: How many individuals on your team are aware of this event?**

Please choose \*only one\* of the following:

- only myself
- only myself and one other team member
- less than half the team
- more than half the team
- the entire team

---

**0003:**

**How did the event take place?**

Please choose \*all\* that apply:

- Physical Meeting (with badges)
- By Email
- By Phone
- Chance Encounter (without badges)
- I was alone on my desk (with setup)
- None of the above

---

**0004:**

**Do you remember the time of the event (for example between 1 pm to 2 pm)? [ Say "No" if you dont]**

Please write your answer here:



---

**0005:**

**Rate the effect of this event on EACH OF THE FOLLOWING:**

Please choose the appropriate response for each item:

very negative effect	moderately negative effect	slightly negative effect	neutral or no effect	slightly positive effect	moderately positive effect	very positive effect
----------------------------	----------------------------------	--------------------------------	----------------------------	--------------------------------	----------------------------------	----------------------------

your feelings about the project	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
your work on the project "today"	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
other team members' work on the project "today"	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
the project overall, in the long-term	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

---

---

**Submit Your Survey.**  
Thank you for completing this survey..

APPENDIX B

IRB APPLICATION AND APPROVAL

Arizona State University Office of Research Integrity and Assurance P.O. Box 871103 Tempe, AZ 85287-1103 Phone: 480-965-6788 Fax: (480) 965-7772		<i>For Office Use Only:</i> Date Received: HS Number:
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## SOCIAL BEHAVIORAL APPLICATION HUMAN SUBJECTS

### PROTOCOL INFORMATION

Protocol Title:  
 Studying Group Work Flow Process

Date: November 3, 2008

### PRINCIPAL INVESTIGATOR (PI)

Please note that the PI's CV and human subject's protection training certification must be attached with this application.

Name and Degree(s):  
 Winslow Burlleson, PhD

Department/Center:  
 School of Computing and Informatics/ Arts, Media, and Engineering

Mailing Address:  
 Arts, Media, and Engineering,  
 Arizona State University,  
 699 S Mill Avenue, room 395  
 Tempe, AZ 85281

Email:  
[Winslow.Burlleson@asu.edu](mailto:Winslow.Burlleson@asu.edu)

Phone:  
 (480) 965-9253

Fax:  
 (480) 965-0961

University Affiliation:  
 Professor  
 Associate Professor  
 Assistant Professor  
 Instructor  
 Other: Please specify. ("Other" categories may require prior approval. Students cannot serve as the PI)

### CO-INVESTIGATORS (CO-I)

- A Co-I is anyone who has responsibility for the project's design, implementation, data collection, data analysis, or who has contact with study participants.
- If the project involves medical procedures or patient care that the PI is not certified or licensed to conduct, a responsible physician or other certified or licensed professional must be included as a Co-I. The application must include a copy of supporting documentation for this individual (CV, license, board certification etc).

Name	Study Role	Affiliation	Department	Email/TeI/Fax	Student (yes/no)
Priyamvada Tripathi	research assistant	department of CSE	Arizona State University	<a href="mailto:pia@asu.edu">pia@asu.edu</a>	yes

### **PROJECT FUNDING**

1a) How is the research project funded? (A copy of the grant application **must** be provided prior to IRB approval)

- Research is **not funded** (Go to question 2)  
 Funding decision is pending  
 Research is **funded**

b) What is the source of funding or potential funding? (Check all that apply)

- Federal                       Private Foundation                       Department Funds  
 Subcontract                       Fellowship                       Other

c) Please list the name(s) of the sponsor(s): National Science Foundation (NSF)

d) What is the grant number and title? 0846148, SGER: Creativity in IT research organizations

e) What is the ASU account number/project number? CSR0 153

f) Identify the institution(s) administering the grant(s): Arizona State University, Massachusetts Institute of Technology

### **PROJECT SUMMARY**

2. Provide a **brief** description of the **background, purpose, and design** of your research. Avoid using technical terms and jargon. Describe all interactions with potential study participants (e.g., how identified, how recruited) including all of the **means you will use to collect data** (e.g. instruments, measures, tests, questionnaires, surveys, interview schedules, focus group questions, observations). Provide a short description of the tests, instruments, or measures. (If you need more than a few paragraphs, please attach additional sheets.) **Attach copies of all instruments and questionnaires. FOR ALL OF THE QUESTIONS, WRITE YOUR ANSWERS ON THE APPLICATION RATHER THAN SAYING "SEE ATTACHED".**

The research comprises of studying teams of 5-7 individuals engaged in a creative activity for 4-6 weeks. A creative activity is defined as any active and non-routine problem solving or generation of novel idea. The individuals report their own experiences before and after each work day on their emotions (Affect) and creative experiences. These reports are organized as journal entries, bullet point survey, and open-ended questions. For example, a questionnaire is intended to get the emotional experience of the participant and hence will ask "how did you feel during the episode (of coming up with a new idea) and will have choices such as happy, sad, depressed, etc. Team valence will be recorded by a TEAM survey that intends to capture the work environment (is it collaborative, conservative, challenging, etc?) and team interaction (happy with the team, the team is making progress, etc.). In the personal project analysis, participants are asked to report the subjective ratings for the importance, progress, challenge, etc. of the project they are participating in. In addition, the participants are given special kind of mouse that records pressure intensity of the clicks. They also wear a bracelet that externally looks like a regular band but inside the rubber outer cover there is a wireless skin conductor that records the temperature of the skin. Occasionally, participants may also be required to sit on a chair that is covered with a black comfortable seat cover but inside the seat cover there are additional pressure sensors that give data on posture of the participant. Socioscopes are a way of using wearable computing devices such as PDA and cell phone to locate a person, upper body movement and ambient audio using embedded speakers and 2d accelerometer that are invisible to the user. This data is designed to collect various facets of person's experience in order to study the relationship between person's affective state and creative output. In addition, the team creativity will be studied from each individual's response.

### **STUDY DURATION**

3. What is the expected duration of the study through data analysis? (Include a timeline, if applicable). 1 year

a. When is the expected date that you wish to begin research? (MM/DD/YY) 11/11/2008 (must be after submission date) Note: Protocols are approved for a maximum of 1 year. If a project is intended to last beyond the approval period, continuing review and reapproval are necessary. Research cannot begin until you have received an approval letter.

### **IRB APPROVAL**

4. Has this project been reviewed by another IRB?  Yes  No (If yes, please complete the information below and attach a copy of the IRB approval materials).

a) What is the name of the institution?

b) What is the current IRB approval date/status of IRB application?

### **STUDY SITES**

5. Where will the study be conducted? (Check all that apply)

On campus (Please indicate building(s) and room number (s) when known) This study involves combination of wearable computing with social science survey. Hence, there is no specific location that is assigned to the participants. The setup for affective sensing is in BYENG AME space (3rd floor) and Digital Arch Ranch 118 where participants will occasionally work on.

Off campus (Please provide location and letter of permission, where applicable)

### **SAMPLE SIZE/DURATION**

6a) What is the expected number of individuals to be screened for enrollment? 40

b) What is the **MAXIMUM** number of subjects that you plan to enroll in the study? 100

c) What is the approximate number of: 80 Males 20 Females

d) Indicate the age range of the participants that you plan to enroll in your study. 18 to 65

e) What is the expected duration of participation for each subject? (at each contact session and total) 15-30 minutes sessions, 5 working days each week for 4-6 weeks.

### **SUBJECTS**

7. Will the study involve any of the following participants? (Please check all that apply if your study specifically targets these populations)

- |   |  |
|---|--|
| <input type="checkbox"/> Children (under 18)    | <input type="checkbox"/> Pregnant women  |
| <input type="checkbox"/> Prisoners or detainees | <input type="checkbox"/> Persons at high risk of becoming detained or imprisoned |
| <input type="checkbox"/> Decisionally impaired  | <input type="checkbox"/> Patients- what is the status of their health?           |
| <input type="checkbox"/> Fetuses                | <input type="checkbox"/> Native Americans  |

Non-English speakers (Include copy of all materials in language of participants and certification of the translation and back-translation: <http://researchintegrity.asu.edu/irb/apply/backtranslation-form.doc> )

a) If any of the above categories have been checked, please state how you will protect the rights and privacy of these individuals.

b) Please provide the rationale for the choice of the subjects including any inclusion criteria.

c) Will any ethnic/racial or gender groups be excluded from this study? If so, provide the rationale for the exclusion criteria. No

### **RECRUITMENT**

8. Describe the process(es) you will use to **recruit participants** and inform them about their role in the study. **(Attach copies of any recruitment materials.)**

An email request will be sent to participants. The participants are generally group of 4 or more people working on a creative project. Most of our participants are expected to be of college undergraduates and graduate students. All are above 18 years of age with no physical or mental disability.

a) Will any of the following be used? **(Check all that apply and attach copies)**

- Internet/Email  
 Newspapers/radio/television advertising  
 Posters/brochures/letters  
 Other

#### **DECEPTION**

9. Does the proposed research require that you deceive participants in any way?  Yes  No

a) If your response is “yes,” describe the type of **deception** you will use, indicate why it is necessary for this study, and provide a copy of the debriefing script. **In our email and instructions, we intend to hide terms like creativity and affect and instead describe the goal of the study to be “work flow process”.** This is necessary to avoid priming the subjects for creative output and emotional tuning. We want to keep the process as normal as possible and suspect that informing the subjects of the main goal will lead to heightened awareness and may bias the data.

#### **COMPENSATION**

10. Will any type of compensation be used? **(e.g. money, gift, raffle, extra credit, etc)**

a)  Yes **(Please describe what the compensation is)**  No (go to question 11)

b) Explain why the compensation is reasonable in relation to the experiences of and burden on participants.

c) Is compensation for participation in a study or completion of the study? **(Note: participants must be free to quit at any time without penalty including loss of benefits).**

Participation  Completion

d) If any of the participants are economically disadvantaged, describe the manner of compensation and explain why it is fair and not coercive.

#### **INFORMED CONSENT**

11. Describe the procedures you will use to **obtain and document informed consent and assent**. **Attach copies of the forms that you will use.** In the case of secondary data, please attach original informed consent or describe below why it has not been included. Fully justify a request for a waiver of written consent or parental consent for minors.

**(The ASU IRB website has additional information and sample consent and assent forms.)**

The consent form is prepared that describes all the issues of data security, promise of privacy and anonymity, and seeks the participation only if the participant is fully willing. It also informs that there are no possible risks involved with the study. It further informs the participant the potential contribution of the study towards scientific progress. The form is attached.

Prior to the study, experimenter will provide a copy of the informed consent and read out the form. Following this, participants will be allowed to ask questions pertaining to their participation. After this, participants will be asked



whether they would like to participate. If yes, the consent form will be signed, and a copy of the signed form will be given to the participant. If no, participants will be respectfully allowed to leave.

### **RISKS**

12. What are the potential risks of the research? (Check all that apply)

- Physical harm
- Psychological harm
- Release of confidential information
- Other

a) Describe any potential risks to human subjects and the steps that will be taken to reduce the risks. Include any risks to the subject's well-being, privacy, emotions, employability, criminal, and legal status. There are no potential sources of harm. The equipment used for the experiment has proven history of safety. Experiments of this nature have been conducted before and do not have a history of any psychological or physical harm. It is a simple experiment that involves wearable computing and social survey data and does not involve any other component. To avoid risks of confidentiality, we do not collect any confidential information. A participant can also choose to unconditionally leave the study midway.

### **BENEFITS**

13a) What are the potential benefits to the individual subject, if any, as a result of being in the study? No personal benefits are rendered to the participants from this study.

b) What are the potential benefits, if any, to others from the study? No benefits are rendered to any personnel from this study.

### **DATA USE**

14. How will the data be used? (Check all that apply)

- |   |  |
|---|--|
| <input checked="" type="checkbox"/> Dissertation                    | <input checked="" type="checkbox"/> Publication/journal article  |
| <input checked="" type="checkbox"/> Thesis                          | <input checked="" type="checkbox"/> Undergraduate honors project |
| <input type="checkbox"/> Results released to participants/parents   | <input type="checkbox"/> Results released to employer or school  |
| <input type="checkbox"/> Results released to agency or organization | <input checked="" type="checkbox"/> Conferences/presentations    |
| <input type="checkbox"/> Other (please describe):                   |  |

### **PROTECTION OF CONFIDENTIALITY**

15. Describe the steps you will take to ensure the confidentiality of the participants and data.

a) Indicate how you will safeguard data that includes identifying or potentially identifying information (e.g. coding). The data gathered during the experiment will be kept in password protected folder and password protected computers whose access is restricted to the investigators of the experiment. No identifying information such as name or social security number will be stored with the data in the dataset. Hard copy will be stored with Dr. W. Burleson at his ASU office. No hardcopy of soft copy will contain any personal information of the participant. Instead, they will be located using file identifies the copy of which will be with Dr. Burleson in protected folder.

b) Indicate when identifiers will be separated or removed from the data. Prior to data collection, each team, location, and participant will be assigned identifiers that will be used for data analysis and collection.

c) Will the study have a master list linking participants' identifying information with study ID codes, and thereby, their data? If so, provide a justification for having a master list. (Note: In many cases, the existence of a master list is the only part of a study that raises it above minimal risk, that is, places participants at risk.)

No.

d) If you have a master list and/or data with identifiers, where on campus will the list and/or data be kept? **(Data sets with identifiers and master lists, whether electronic or in hard copy, should be securely stored on an ASU campus except in unusual circumstances (e.g., research conducted out of the state or country).)**

e) If you have a master list, when will it be destroyed? Yes, the list will be destroyed after collection of the data. A key identifier will be assigned to the data set.

f) How long do you plan to retain the data? Maximum 6 years.

g) How will you dispose of the data? The soft copies will be permanently deleted. We plan to have no additional copies of data but it might be necessary occasionally to work on different computers in which case soft copies will be temporarily copied and work with and permanently deleted after the work is done. Steps will be taken to ensure that all hard copies are permanently destroyed. The media will be collected from the equipment at the end of each day and equipments will be cleared of any data.

h) Where on campus will you store the signed consent, assent, and parental permission forms (If applicable)? **(Consent, assent, and parent permission forms should be securely stored on an ASU campus except in unusual circumstances.)** They will be kept in Dr. Burlleson's ASU office.

### **INVESTIGATOR INTERESTS**

16. Does the investigator have a current conflict of interest disclosure form on file at the ASU Research Compliance Office?  Yes  No

a) Do any of the researchers or their family members, have a financial interest in a business which owns a technology to be studied and/or is sponsoring the research?  Yes  No (If yes, please describe and disclose in the consent form.)

b) Are there any plans for commercial development related to the findings of this study?  
 Yes (If yes, please describe.)  No

c) Will the investigator or a member of the investigator's family financially benefit if the findings are commercialized?  
 Yes (If yes, please describe.)  No

d) Will participants financially benefit if the findings are commercialized?  
 Yes (If yes, please describe.)  No

### **BIOLOGICAL MATERIALS**

17a) Will biological materials be collected from subjects or given to subjects?  Yes  No (If no, please skip to question 18)

b) Provide a description of the material (blood, tissue, vectors, antibodies, etc.) that will be used:

c) If the study involves human blood, do you have the required ASU Biosafety disclosure on file?  Yes  
 No (If yes, what is the Biosafety Disclosure number.)

d) Will any of the material being used in the study come from a third party?  Yes  No (If yes, attach copy of the Material Transfer Agreement if required.)

e) Does this study involve transfer of genetic material of animal tissue into humans?  Yes  No  
(If yes, please cite the ASU Institutional Biosafety Disclosure number).

### TRAINING

18. The research team must document completion of human subjects training. (Attach a copy of the NIH Certificate for Human Participants Protections Education for Research Teams or CITI Training: <http://researchintegrity.asu.edu/irb/training/> for the PI and all Co-Investigators.)

Please provide the date that the PI and co-investigators completed the training. Priyamvada Tripathi  
09/10/2004.

### PRINCIPAL INVESTIGATOR

In making this application, I certify that I have read and understand the ASU Procedures for the Review of Human Subjects Research and that I intend to comply with the letter and spirit of the University Policy. Changes in to the study will be submitted to the IRB for written approval prior to these changes being put into practice. **I also agree and understand that informed consent/assent records of the participants will be kept for at least three (3) years after the completion of the research. Attach a copy of the PI's CV unless one is already on file with the Office of Research Integrity and Assurance.**

Name (first, middle initial, last):  
Winslow Burlerson

Signature:

Date: November 3, 2008

<b>FOR OFFICE USE:</b>	This application has been reviewed by the Arizona State University IRB: <input type="checkbox"/> Full Board Review <input type="checkbox"/> Expedite Categories: <input type="checkbox"/> Exempt Categories:  <input type="checkbox"/> Approved <input type="checkbox"/> Deferred <input type="checkbox"/> Disapproved  <input type="checkbox"/> Project requires review more often than annual Every _____ months
	Signature of IRB Chair/Member: _____ Date: _____

**To:** Winslow Burleson  
BYENG

**From:** Mark Roosa, Chair *sm*  
Soc Beh IRB

**Date:** 10/29/2010

**Committee Action:** Renewal

**Renewal Date:** 10/29/2010

**Review Type:** Expedited F7

**IRB Protocol #:** 0810003396

**Study Title:** Creativity in IT Research Organizations

**Expiration Date:** 10/28/2011

The above-referenced protocol was given renewed approval following Expedited Review by the Institutional Review Board.

It is the Principal Investigator's responsibility to obtain review and continued approval of ongoing research before the expiration noted above. Please allow sufficient time for reapproval. Research activity of any sort may not continue beyond the expiration date without committee approval. Failure to receive approval for continuation before the expiration date will result in the automatic suspension of the approval of this protocol on the expiration date. Information collected following suspension is unapproved research and cannot be reported or published as research data. If you do not wish continued approval, please notify the Committee of the study termination.

This approval by the Soc Beh IRB does not replace or supersede any departmental or oversight committee review that may be required by institutional policy.

**Adverse Reactions:** If any untoward incidents or severe reactions should develop as a result of this study, you are required to notify the Soc Beh IRB immediately. If necessary a member of the IRB will be assigned to look into the matter. If the problem is serious, approval may be withdrawn pending IRB review.

**Amendments:** If you wish to change any aspect of this study, such as the procedures, the consent forms, or the investigators, please communicate your requested changes to the Soc Beh IRB. The new procedure is not to be initiated until the IRB approval has been given.

**CONSENT FORM**  
**Studying Group Work Flow Process**

**INTRODUCTION**

The purposes of this form are to provide you (as a prospective research study participant) information that may affect your decision as to whether or not to participate in this research and to record the consent of those who agree to be involved in the study.

**RESEARCHERS**

Priyamvada Tripathi, graduate student, Department of Computer Science and Engineering, and Winslow Burleson, assistant professor, Department of Computer Science and Engineering have invited your participation in a research study.

**STUDY PURPOSE**

The purpose of the research is to study the interactions and work flow characteristics of a group working together.

**DESCRIPTION OF RESEARCH STUDY**

You must be 18 yrs or older in order to participate in this study. If you decide to participate, then you will join a study involving research on work flow. In the study you will be expected to answer few questions related to your productivity and team work in the form of an end of the day survey. In addition, we will record some physiological data such as body temperature, facial expression, and interaction patterns while you are working on the assigned project. The sensors that are used in the study are a form of 'wearable computing' just like your cellphone. They capture digital information about your location, interactive environment, and activity patterns. These patterns will help us support the self-reports with other data and derive some useful results on work flow within a group.

If you say YES, then your participation will last approximately 1 month. During this month, you will be wearing a pda like device on your neck that records your interaction patterns such as it will detect when you meet other members of your group and how long. It will also record the tone of your speech (exact contents will not be recorded). You can turn the device on or off through a simple switch at your will. You do not need to use the device while working on other projects. A small survey will be delivered via email to you every evening. It requires additional 15 to 30 minutes of your time per day you work on the chosen project. Almost all survey questions are optional. However, since we have constructed a survey around a set of scientific questions, you are encouraged to complete the survey as much as possible. At the end of few sessions of work (each session is a on/off cycle), you may need to turn in the device so we can empty the data from it and make it ready for reuse.

**RISKS**

There are no known risks from taking part in this study, but in any research, there is some possibility that you may be subject to risks that have not yet been identified.

**BENEFITS**

Although there may be no direct benefits to you, the possible benefits of your participation in the research are increased knowledge on behavioral mechanisms underlying work flow process. The study may also help you by giving you insights into your work patterns and opportunities to include habits that might improve your productivity. At the end of the study, you will have the opportunity to discuss our results and ask detailed questions on how it affects you.

**CONFIDENTIALITY**

All information obtained in this study is strictly confidential. The results of this research study may be used in reports, presentations, and publications, but the researchers will not identify you.

The name and age group of the participant will not be revealed to any one other than the researchers (Dr. Winslow Burleson and Priyamvada Tripathi) involved in the project. The researcher will note the

responses of the participant on the computer file with the identification number. Dr. Winslow Burleson will have the names and its matching identification number. Data will be strictly used for statistical analysis and never be discussed on individual level.

The data gathered during the experiment will be kept in password protected folder and password protected computers whose access is restricted to the investigators of the experiment. You are not required to divulge any secure information such as social security number during your participation.

**WITHDRAWAL PRIVILEGE**

Participation in this study is completely voluntary. It is ok for you to say no. Even if you say yes now, you are free to say no later, and withdraw from the study at any time. Your decision will not affect your relationship with Arizona State University and any other institution or otherwise cause a loss of benefits to which you might otherwise be entitled. This includes your grades as a student or employment status, treatment, care etc.

**COSTS AND PAYMENTS**

The researchers want your decision about participating in the study to be absolutely voluntary. There is no payment for your participation in the study.

**VOLUNTARY CONSENT**

Any questions you have concerning the research study or your participation in the study, before or after your consent, will be answered by Priyamvada (Pia) Tripathi email pia@asu.edu and Winslow Burleson, email Winslow.burleson@asu.edu.

If you have questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk; you can contact the Chair of the Human Subjects Institutional Review Board, through the Office of Research Integrity and Assurance, at 480-965 6788.

This form explains the nature, demands, benefits and any risk of the project. By signing this form you agree knowingly to assume any risks involved. Remember, your participation is voluntary. You may choose not to participate or to withdraw your consent and discontinue participation at any time without penalty or loss of benefit. In signing this consent form, you are not waiving any legal claims, rights, or remedies. A copy of this consent form will be offered to you.

Your signature below indicates that you consent to participate in the above study.

\_\_\_\_\_  
Subject's Signature

\_\_\_\_\_  
Printed Name

\_\_\_\_\_  
Date

**INVESTIGATOR'S STATEMENT**

"I certify that I have explained to the above individual the nature and purpose, the potential benefits and possible risks associated with participation in this research study, have answered any questions that have been raised, and have witnessed the above signature. These elements of Informed Consent conform to the Assurance given by Arizona State University to the Office for Human Research Protections to protect the rights of human subjects. I have offered the subject/participant a copy of this signed consent document."

Signature of Investigator \_\_\_\_\_

Date \_\_\_\_\_

ASU IRB Approved
Sig <u>SM</u>
Date <u>10/29/10 - 10/28/11</u>