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Active and Passive User Trust in Sociotechnical Systems

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14. ABSTRACT
Active and passive user is a way to understand how users can have different perspectives of the use of technologies in complex socio-technical systems. These different perspectives can influence how trust is formed and calibrated for individual users and teams of users. As a result, appropriate use, misuse, disuse, or abuse of technology may occur. This project pioneered the research in active passive user systems through a series of experimental studies. The goals of the project were to understand: (1) pair-level factors that shape trust, (2) psychophysiological markers that predict trust, (3) user characteristics that relate to trust, and (4) the affective process of trust.
This final report included four major experiments that addressed the four goals. In those four experiments, participants worked as two-person teams consisted of one active user and one passive user and multi-tasked using a modified version of Multi Attribute Task Battery (MATB) with a shared computer station.

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1. Summary

Active and passive user is a way to understand how users can have different perspectives of the use of technologies in complex socio-technical systems. These different perspectives can influence how trust is formed and calibrated for individual users and teams of users. As a result, appropriate use, misuse, disuse, or abuse of technology may occur. This project pioneered the research in active passive user systems through a series of experimental studies. The goals of the project were to understand: (1) pair-level factors that shape trust, (2) psychophysiological markers that predict trust, (3) user characteristics that relate to trust, and (4) the affective process of trust.

This final report included four major experiments that addressed the four goals. In those four experiments, participants worked as two-person teams consisted of one active user and one passive user and multi-tasked using a modified version of Multi Attribute Task Battery (MATB) with a shared computer station.

The first study identified a list of antecedents of trust in technology using qualitative analysis techniques. The following main categories emerged as the antecedents: technology factors, user factors, and task factors. Similarities and differences between active users and passive user responses, in terms of trust in technology were further identified. The second study examined the relationship between physiological compliance (PC) and trust in technology. The results showed that PC relates to a shared perception of trust in technology among the team members. This supported the notion that PC can be a useful tool for monitoring team process, even for trust calibration. The third study explored user characteristics that relate to trust for active and passive users. The results indicated that in trust calibration between active and passive users, dispositional factors, e.g., computer anxiety, were important for the active users, while interactions between the active user and the passive user, and between the active user and the technology were more influential for passive users. The fourth study manipulated participants' incidental affect and measured their integral affect to understand the how affective process influences trust. The results indicated that positive integral affect positively related to trust in technology. Incidental affect influenced trust in technology, however, this effect was moderated by positive integral affect. Positive integral affect also mediated the relationship between technology/task conditions and trust in technology. The findings from the four studies reveal important mechanisms of trust calibration process in active passive user teams and have implications for system design.

2. Research goals

A passive user is an individual who has limited direct control of technologies and artifacts in a work system (Montague & Xu, 2012). The opposite concept is the active user who actively controls the technological environment. Examples of systems that consist of both passive and active users include: customers (passive user) and service providers (active user) in face-to-face service encounters (Inbar & Tractinsky, 2010); Pilots not flying (passive user) and pilots flying (active user) in commercial airplane cockpits; students (passive user) and teachers (active user) in a classroom; and patients (passive user) and physicians (active user) in a clinical encounter (Montague, Winchester III, & Kleiner, 2010).

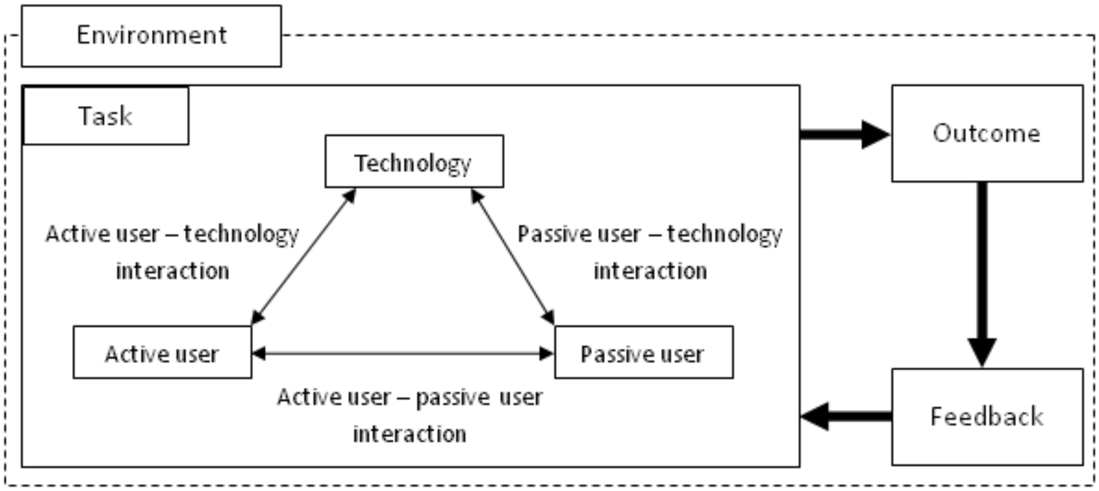

Figure 1. A general conceptual model of a system involving a passive user.

Understanding active and passive user is critical for designing effect technologies used in many multi-user systems and optimizing the outcome of such systems. However, little empirical research have been conducted to understand passive use of technology (Inbar & Tractinsky, 2009), thus there are insufficient design guidelines or principles for designing related technologies and systems. First of all, passive users often exist in teams, where a small group of people with specific roles work interdependently towards a common and valued goal (Salas, Dickinson, Converse, & Tannenbaum, 1992). Team process includes task work as well as teamwork (C.A. Bowers, Braun, & Morgan, 1997). Teamwork refers to mental models, attitudes, and behaviors that facilitate the coordination among the team members (Sims, Salas, Burke, & Wheelan, 2005). In a technologically complex system, teams with passive users may require different and more intensive teamwork among the team members. This is because passive users may have a very different route to develop and maintain their mental models and attitudes about the system comparing to the active users, and this route may largely go through teamwork. For example, in an exploratory study, Montague and Xu (2012) found that active user and passive user's trust in technology is related to different factors – teamwork related factors, such as communication and observation of behavior, are most important predictors for passive users' trust in technology.

The goals of this project were to understand the trust in such active and passive user systems. Specifically:

1) Investigate empirically pair-level factors (with active and passive users) that shape trust in automation through experimental studies.
2) Establish psychophysiological markers for individual and pair level trust in automation to understand the predictors of shared and unshared reliance.
3) Conduct research to understand the impact of shared characteristics on shared trust. Specifically, the impact of age, expertise, personality and propensity to trust on shared trust.
4) Investigate affect empirically as a pair-level factors (with active and passive users) that may shape trust in automation through experimental studies.

3. Background

3.1. Trust in active and passive users systems

3.1.1. Trust in technology

Trust is a fundamental factor in all relationships (Montague, 2010). In social-technical systems, there are three types of trust that are critical for optimal system outcomes: interpersonal trust, trust between two or more people (Larzelere & Huston, 1980), institutional trust, a person's trust with an organization (Castelfranchi & Falcone, 2001), and technological trust, a person's trust with a technology or device (Muir, 1987). Specifically, trust in technology is "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (J. D. Lee & See, 2004). Research in trust in technology continues to grow in the field of Human Factors and Ergonomics as it plays a vital role in human-technology interaction (P. Madhavan & Wiegmann, 2007; Parasuraman & Wickens, 2008).

Previous research has found that a user's level of trust in technology influences the user's strategy towards the use of the technology (Bagheri & Jamieson, 2004; J. D. Lee & Moray, 1994; Muir, 1987). Inappropriate trust in technology can potentially lead to misuse and disuse of the technology (Parasuraman & Riley, 1997). Over trust of technology often results in misuse of technology that leads to complications and errors in the work system. On the other hand, lack of trust in technology prevents the user from utilizing the system to its full extent, and can lead to a decrease in productivity. Recently, there have been efforts to integrate the concept of trust in technology with the technology acceptance model (Ghazizadeh, Lee, & Boyle, 2012; Pavlou, 2003; W. Wang & Benbasat, 2005) to predict a user's intent or behavior to adopt technologies. In addition, an individual's trust in technology may also influence his/her trust in other elements of the system, such as interpersonal trust and institutional trust (Muir, 1994). This issue is critical for industries such as healthcare (Montague & Lee, 2012) and e-commerce (M. K. O. Lee & Turban, 2001) where interpersonal trust and institutional trust are important.

Human factors researchers have investigated the means for trust calibration (J. D. Lee & See, 2004) and how users develop an appropriate level of trust toward the technology. In order to develop effective means for trust calibration, one needs to first identify the antecedents of trust in technology. Researchers have identified a wide variety of factors that influence an individual user's level of trust in technology. Among those factors, reliability of the technology was widely cited in trust in automation studies (Bisantz & Seong, 2001; J. D. Lee & Moray, 1992; Lewandowsky, Mundy, & Tan, 2000; P. Madhavan, Wiegmann, & Lacson, 2006). Factors related to interface design were also identified, such as etiquette (Cassell & Bickmore, 2000; Parasuraman & Miller, 2004), usability (Corritore, Kracher, & Wiedenbeck, 2003; Koufaris & Hampton-Sosa, 2002), social presence (Hassanein & Head, 2004), and visual design (Fogg et al., 2003; Kim & Moon, 1998; Weinstock, Oron-Gilad, & Parmet, 2012). Furthermore, factors related to individual difference, such as age (Sanchez, Fisk, & Rogers, 2004) and propensity to trust technology (Merritt & Ilgen, 2008), were also investigated.

3.1.2. Trust and shared technology

The concept of trust in technology has been previously explored by researchers in work on trust between users and automation (J. D. Lee & See, 2004), information technology (Marsh & Dibben, 2005), and the world wide web (Egger, 2001; Y. D. Wang & Emurian, 2005). However, the majority of current research on trust in technology focuses on situations that involve an individual user's interactions with a technology. When multiple people or groups use a technology, trust in technology could be a factor that influences how the technology is used and collaboration between group members. For example, whether or not the team trusts the technology appropriately can affect overall team performance (C. A. Bowers, Oser, Salas, & Cannon-Bowers, 1996).

Trust in technology at the group level is especially relevant for multi-user shared technologies, such as health technologies shared by physicians, nurses, and patients, or interactive interfaces shared by customer service representatives and customers, or robots used by a military team. Under such shared technology scenarios, the users of the technology sometimes act as active users, who have direct control over the technology, or passive users, who do not have direct control but interact with both the technology and the active users (Inbar & Tractinsky, 2009, 2012; Montague & Xu, 2012; Xu & Montague, 2012). A related concept discussed in the use of technology on the individual level is supervisory control (Sheridan, 2002). Furthermore, if the primary task of the user is monitoring task, then the user is considered to be a passive process operator (Persson, Wanek, & Johansson, 2001). This role of the individual user is characterized by indirect control of task process through automated systems. At the group level the role of individual users can be further differentiated where a passive user of a shared technology is characterized by indirect control of the technology through the active user. For example, in a face-to-face customer service encounter, the customer service representative plays the active user role and the customer plays the passive user role (Inbar & Tractinsky, 2010). The case is similar for the patient and the clinician's roles with regards to the use of computers in a clinical encounter (Montague & Xu, 2012). In other circumstances, an individual could be an active user for some aspects of the shared technology while a passive user to other aspects. An example of this could be the roles of two pilots in a commercial aircraft cockpit. Also the active/passive user roles may switch among individuals during the interaction process; collaboration in robotic surgeries (Hanly et al., 2006) could be an example of such cases.

Previous research has found that active users and passive users have different ways of calibrating trust. Specifically, active users' trust is influenced primarily by trust in the co-user and by direct interaction with the technology, while passive users' trust is influenced by the communication with the active users (Montague & Xu, 2012). However, little research had been conducted to investigate antecedents of trust in technology in the use of a shared technology. It is unclear that previous identified antecedents of trust in technology in single-user scenarios can be applied to multi-user scenarios. Thus, further research is needed to better understand trust in technology from differing perspectives in multi-user systems.

4. Study design and main findings

4.1. Study design overview

Participants worked as two-person teams in the experiment. Teams consisted of one passive user and one active user. These roles were randomly assigned. The active user had full access to the control devices of the computer, including the keyboard and the joystick. The passive user did not have access to any of the control devices but he/she could monitor the tasks and communicate with the active user to assist with the task. The participants were instructed that all of the responsibilities of the task, such as decision making and planning, except physical control, would be shared equally between the two team members. During the experiment, the two participants in a team would share a computer station to perform the task (see Figure. 2).

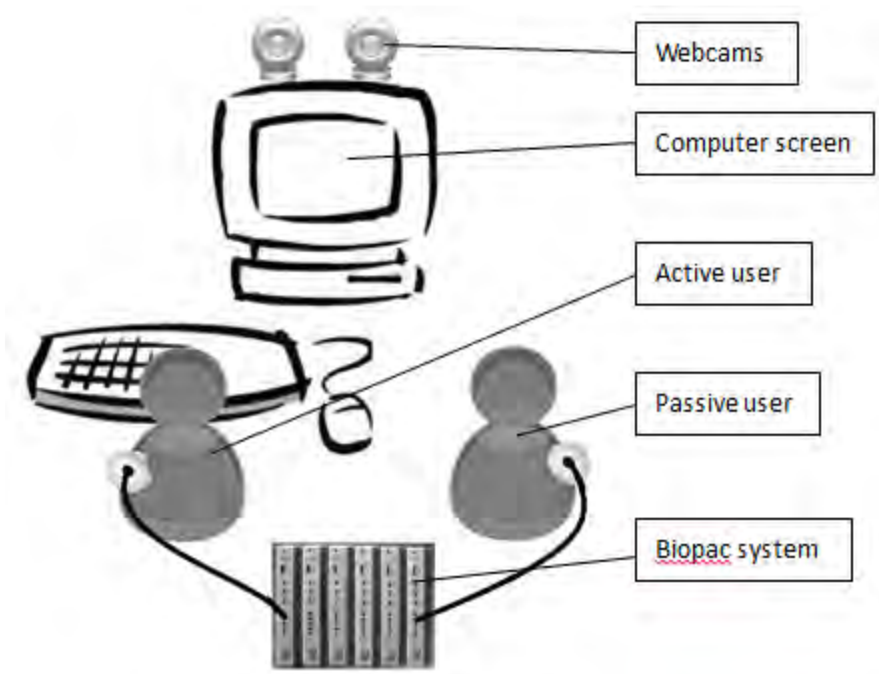

Figure. 2. The setting for the two participants during the experimental sessions.

A modified version of the Multi Attribute Task Battery (MATB) program (Comstock & Arnegard, 1992) was used in this study (see Figure. 3). The participants had to perform three tasks simultaneously in MATB: the monitoring task, the tracking task, and the resource management task. The monitoring task required the participants to respond to two lights and fluctuations of four dials as quickly as possible. The tracking task required the participants to keep a moving target in the center of the screen using a joystick. The resource management task required the participants to control eight pumps to maintain optimum liquid level in two tanks.

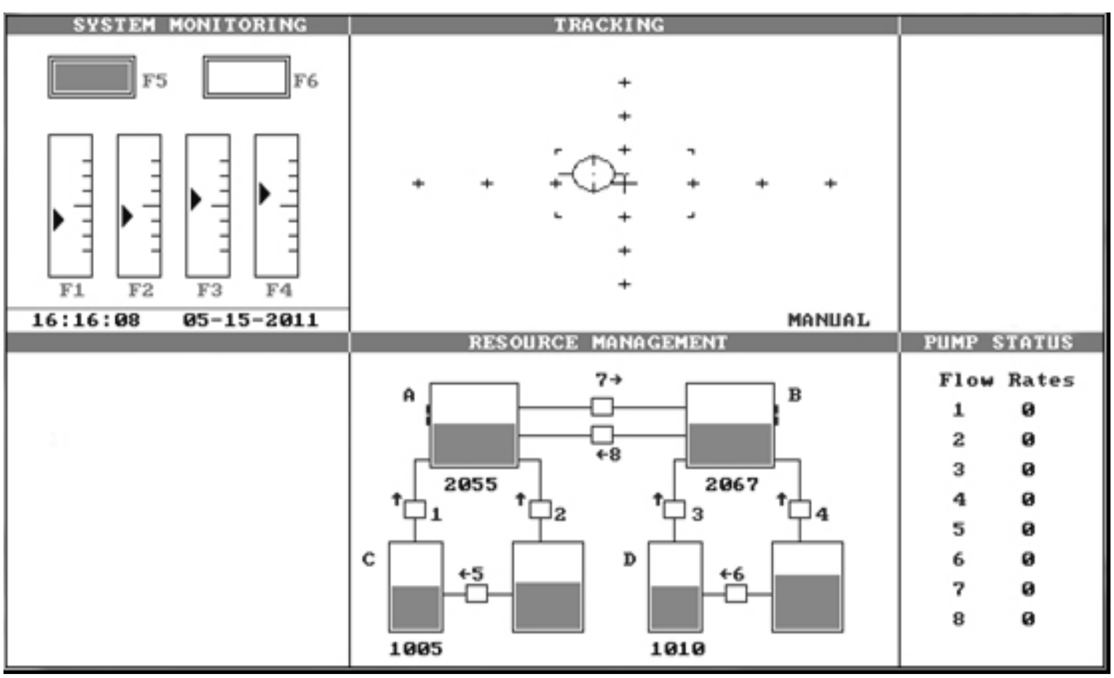

Figure. 3. The interface of the updated and revised Multi Attribute Task Battery (MATB) program.

Each of the teams went through three technological/task conditions in three trials in the experiment – normal condition (N), hard condition (H), and low reliability condition (L). The normal condition was characterized by moderate task difficulty and high technology reliability. The hard condition was characterized by increased difficulty in the monitoring and tracking tasks, compared to the normal condition. In the monitoring task, a more frequent response was required for both the lights and the fluctuation of the dials. In the tracking task, the random movement of the target was increased in both speed and direction change. The low reliability condition was characterized by low reliability of the technology being used – some of the pumps in the resource management task were out of control and it was not possible to maintain optimum liquid level in one of the tanks. The difficulty levels of the other two sub-tasks in this condition were the same as those found in the normal condition. Each trial took the participants six minutes to complete. To prevent order effects related to how the user completed the task, the conditions were counter-balanced across teams with different orders: N-H-L, H-L-N, L-N-H, N-L-H, H-N-L, and L-H-N.

Instruction documents about the MATB and the task were given to the participants to read. The documents included instructions about how to control the computer and the MATB, and the goal of each task in MATB. Next, the program was displayed on the computer and the tasks were explained again orally by the experimenter. Then the participants went through a six-minute individual training session with the program using separate computers. After the training had been completed, the first trial of the task began. The two participants in a team sat next to each other and shared a computer screen to perform the tasks. There were three trials in total. Each trial terminated automatically after six minutes. After each trial, both the active and passive user completed questionnaires separately. After all three task trials had been completed, the participants were given a debriefing statement about the background and purpose of the study.

4.2. Study 1: pair level factors of trust (goal 1)

4.2.1. Research questions

In the human-computer interaction domain, the prominence-interpretation theory proposed by Fogg (2003) could provide a framework for understanding how different factors affect user's trust. As shown in Figure. 4, the process of trust calibration involves two elements, namely prominence and interpretation. Prominence refers to the likelihood of a specific system element being perceived by a user. Interpretation refers to how a user evaluates the system element in terms of trust. The overall trust of the user towards the technology is the combined effect of the factors that are perceived by the user and the user's corresponding evaluation of the system factors. The prominence and interpretation are related to subjective perceptions of the user about the technology, and these perceptions are influenced by objective factors, such as the task being performed, user expertise, and individual differences, etc. (Fogg, 2003). So the collection of system elements that could potentially affect a user's trust in technology becomes a pool of potential antecedents of trust in technology. However, these system elements have to be perceived and evaluated by the user in order to have impact on the user's trust. In addition, the users' roles in the group (whether active or passive user) may affect the users' prominence as well as interpretation of system elements since different users interact with the technology in different ways.

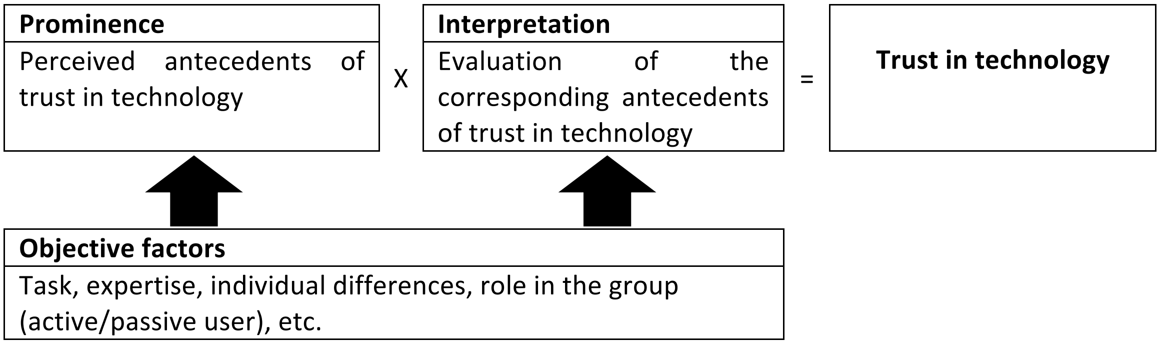

Figure. 4. Prominence-interpretation theory.

The purpose of this experimental study was to understand the antecedents of users' trust in technology in a multi-user system involving active users and passive users. First, as a comparison of general levels of trust in technology of the active user and passive user, a quantitative scale for trust in technology was used in the experiment to answer the following question:

(a) What is the effect of being an active user or a passive user of a shared technology under varied technological/task conditions on the ratings of trust in technology?

To further understand the antecedents of trust in technology in such a setting, qualitative data was collected and analyzed. Prominence and interpretation related to a user's trust in technology was investigated through open ended questions about the factors (prominence) that led the user to trust/distrust (interpretation) the technology. The following research questions were addressed:

(b1) What are the antecedents of trust in technology reported by the users?

(b2) What are the similarities and differences in reported antecedents of trust in technology from the active users and the passive users?

(b3) How do the technological/task conditions influence the type of antecedents of trust in technology reported by the user?

Finally, the quantitative data and qualitative data were integrated to answer the following research question:

(c) What is the relationship between the rating of trust in technology and the reported antecedents of trust in technology?

4.2.2. Participants

Participants of the study were recruited from a human factors introductory course at a large Midwestern university in the US through voluntary sign up. The sample size was 54 in 27 two-person teams. 36 participants (66.7%) were male. The age of the participants ranged from 19 to 29, with the average of 21.6 (SD=1.6). As compensation for participating in the study, participants were given extra credit points in a specific course. As an incentive for the study, there was a $20 reward for each of the team members in the best performing team in this study.

4.2.3. Procedure

The general procedure was the same as the description in section 4.1.

Questionnaires were given after each task trial in order to gather participants' subjective experiences of the technology. A trust in technology scale (Jian, Bisantz, & Drury, 2000) was used for measuring trust quantitatively and an open ended question was used for eliciting why the participants trust or distrust the technology qualitatively. The question was phrased as follows: "Do you trust the technology to perform the task? Why or why not?" At the end of the experiment, the participants were asked to fill out a questionnaire which included demographic information questions and a 14-item task motivation scale. The task motivation scale was derived from the Dundee Stress State Questionnaire (Matthews et al., 2002).

4.2.4. Results

Technological/task conditions, roles, and technological/task conditions X roles interaction were entered into a linear mixed effect (LME) model to predict average trust in technology rating. Participants nested in teams were entered as a random intercept. Significant main effects for technological/task conditions were found ($F(2, 104) = 11.85$, $p < 0.00$). Specifically, mean average trust in technology ratings was significantly lower in the low reliability condition than that in the normal condition ($t(104) = 2.49$, $p = 0.01$). No significant effects were found for roles and technological/task conditions X roles interaction. The results are visualized in Figure. 5.

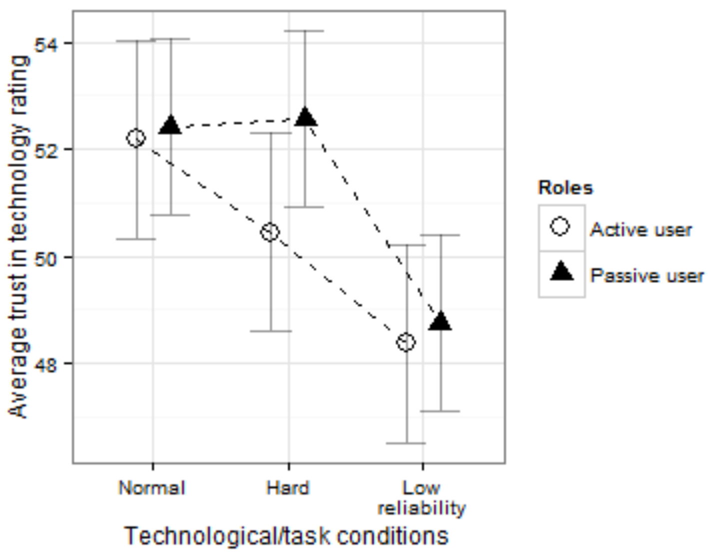

Figure. 5. The effect of technological/task conditions and roles on average trust in technology rating.

The open ended question regarding why the participants did or did not trust the technology was analyzed qualitatively. A total number of 16 codes emerged from the data. These codes were labeled as first level factors. The first level factors were further organized into six second level factors according to their similarities. Finally, the second level factors were organized into three third level factors to represent different aspects of a system. The three third level factors included technology, user, and task factors. The technology factor focused on the computer being used. This involved three second level factors, including usability, competence, and appearance/aesthetics of the technology. The user factor included the participant's personality and confidence in using the technology. The task factor included the tasks being performed, emphasizing what the demands of the tasks were, as well as the outcomes of the tasks. Table 1 also shows the definitions of the codes and how they were categorized into different levels of factors. An example of quotes from the participants was also provided for each of the codes in the table.

Table 1. Codes and their definitions and categories, with quotes from the responses of the participants.

Third level factors	Second level factors	First level factors	Definition	Example survey response from user (Active user (A)/Passive user (P))
Technology factor	*Usability*	Ease of use	if the system is easy to use in general	"It requires much to do to perform the task. Need to be more user friendly." (A)
		Display	if the user can easily see information/signals regarding the task	"It is a good indicator of what is happening." (P)
		Control	if the control of the system requires low levels of effort and is accurate	"We have to do all the work for it." (P)
		Feedback	if the system indicates that it has received user input	"Feedback from the F1-F4 keys and the lighting on the bottom part helped in knowing my commands were executed." (A)
		Error	if the user can easily make an error while using the system	"The technology is prone to error than can result from misjudging a signal or pressing the wrong button." (A)
		Learnability	if the use of the system can easily be learned	"Given enough time, you can learn and master the system." (P)
	Competence	Automation	if the system can perform the task with higher level of automation	"It doesn't auto-correct mistakes." (P)
		Flexibility	if the system can be used in a variety of situations	"Coding could be built in for alarms that can handle more system awareness of each component all at once." (P)
		Reliability	if the system is providing accurate information to the user	"I think the pumps may be working at a different speed than it says." (A)
		Consistency	if the system behaves consistently	"It shows consistent results with what I have asked for." (P)
		Efficiency	if the system responds to the user in a timely manner	"When it was given cues, it completed the task in a timely manner." (P)
	Appearance	Appearance	if the system's appearance and documentation appears well designed and sophisticated	"It is a very complex system that seems to work well." (P)
User factor	*Individual differences*	Confidence	if the user is confident in their abilities and performance	"I cannot control it fast enough." (A)
		Personality	if the user tends to trust technology in general	"Yes, I have a lot of trust in technology and typically think things were programed correctly." (P)
Task factor	*Demand*	Demand	if the task(s) is demanding in terms of multi-tasking or difficulty	"It is hard to take in so much information that is always changing quickly, so I would only trust it to a fairly minimal level." (A)
	Outcome	Outcome	if the outcome of the error is severe	"If something goes wrong, there is an accountability nightmare." (P)

In the subsequent analysis, second level factors were used to represent the reported antecedents of trust in technology, in order to balance amount of information and simplicity of the analysis. Figure. 6 shows frequency counts of the coded second level factors as they related to reported trust/distrust in technology. To test the relationship between second level factors and trust/distrust in technology, a generalized linear mixed model (GLMM) was fitted to the data. Trust/distrust in technology was entered as the response variable with binomial distribution and logit link function. Second level factors were entered as predictor variables. In addition, roles, technological/task conditions, and roles X technological/task conditions interaction were also entered as predictor variables. Since there were instances where multiple second level factors were coded from the answer of one trial, the structure of the random intercept was that trials nested in participants and in turn nested in teams. Wald test for the model coefficients indicated that there was a significant second level factors effect on trust/distrust in technology ($\chi^2(df=6)=1.50\times10^{12}, p<0.00$). This result suggested that different antecedents of trust in technology related to the dichotomous report of trust or distrust in technology to a different extent. On the other hand, the effects of roles (t(26) = 1.20, p = 0.26) and technological/task conditions ($\chi^2(df=2)=2.60, p=0.27$) were not significant.

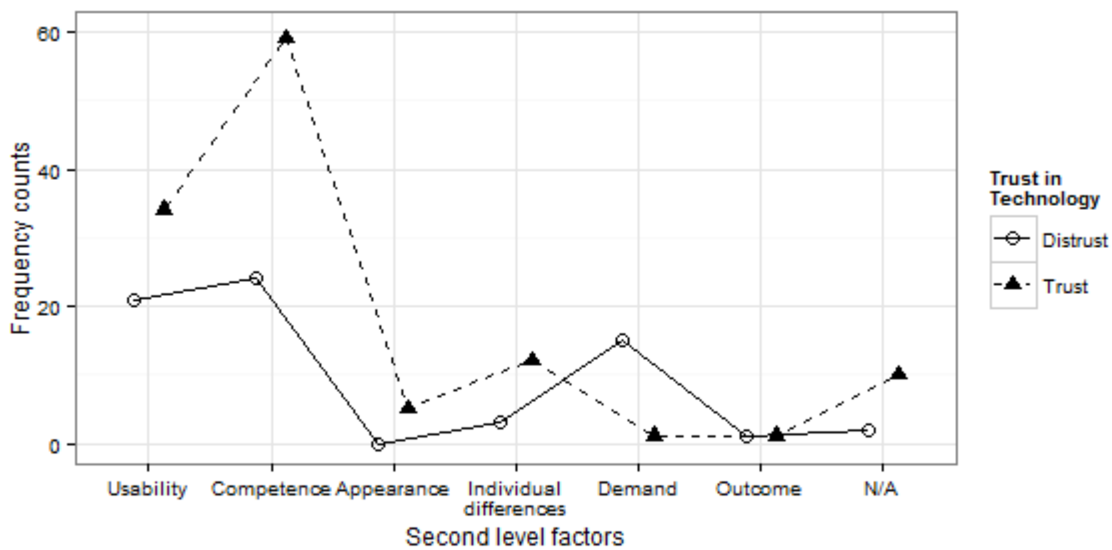

Figure. 6. The frequency counts of the second level factors by trust/distrust in technology. “N/A” represents the instances that no codes were generated from the open ended question.

Figure. 7 shows the frequency counts of the second level factors at different levels of the two independent variable – roles and technological/task conditions. To explore the relationship between the second level factors and the independent variables, a technique known as surrogate Poisson model analysis (Venables & Ripley, 2002) was used. First, a “minimal model” was fitted to the data. The model was specified as a generalized linear model with Poisson distribution and log link function for the response variable. Frequency counts were used as the response variable. The predictor variables include roles, technological/task conditions, roles X technological/task conditions interaction, and second level factors. AIC of the minimal model was 162.19. Residual deviance of the model was 26.20 with 30 degrees of freedom. Second, two predictor variables – roles X second level factors interaction and technological/task conditions X second level factors interaction – were added to the minimal model to test if there was a significantly better fit. If there was a significantly better model fit, it indicates that there should be a relationship between the second level factors and the independent variables, and this relationship affects the distribution of the frequency count. The resultant model by adding roles X second level factors interaction had an AIC of 163.07. The resultant model by adding technological/task conditions X second level factors interaction had an AIC of 176.13. None of the new models suggested a better fit to the data. So no relationship was found between the second level factors and the independent variables in this analysis.

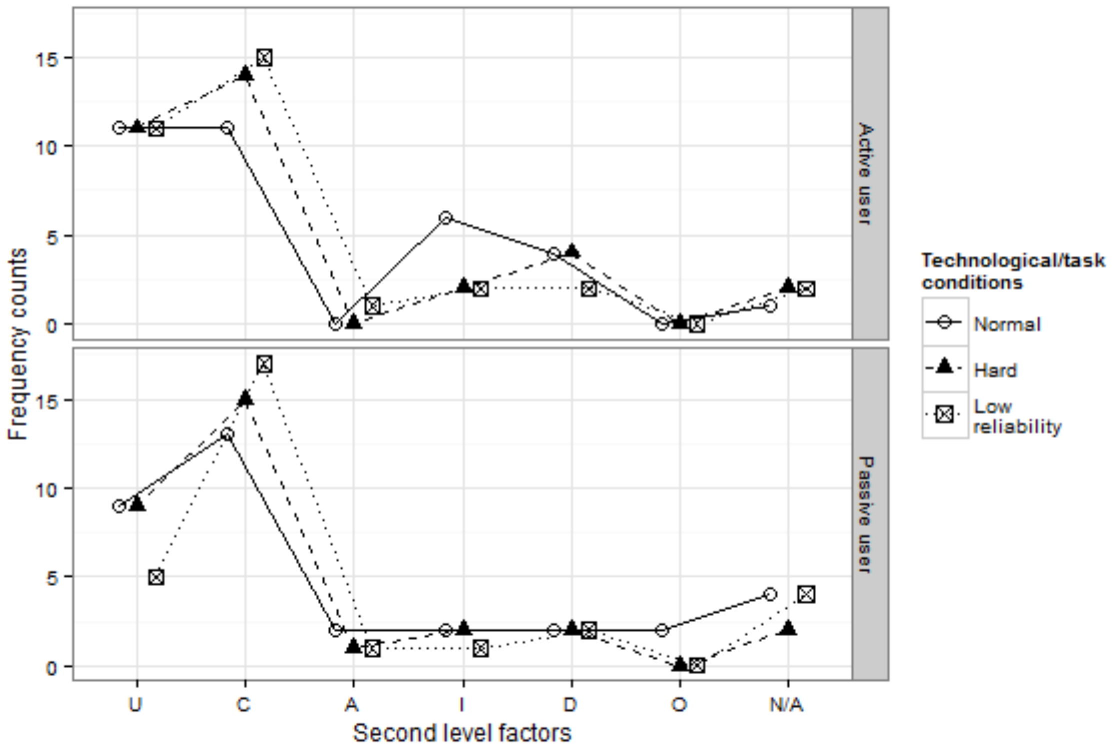

Figure. 7. The frequency counts of the second level factors by different roles and technological/task conditions. “U”, “C”, “A”, “I”, “D”, “O” represent usability, competence, appearance, individual differences, demand, and outcome, correspondingly. “N/A” represents the instances that no codes were generated from the open ended question.

4.2.5. Discussion

The analysis of overall trust in technology ratings provided insight into research question (a). The finding was consistent with previous research (Montague & Xu, 2012) that there was no significant difference between the active user and passive user on average. That is to say, on average, the passive users reported a similar level of trust in technology as the active users reported under varied technological/task conditions. It appears that the active user and passive user in a team calibrated their trust in technology to a similar extent through interaction, even though they may or may not have explicitly discussed the trustworthiness of the technology. Future research could explore the content of the communications between the active user and the passive user in a team and examine how these communications contribute to the calibration of trust at the team level. For example, Xu and Montague (2013) found that group polarization happened after group discussion of the trustworthiness of the technology. Moods, which are heavily influenced by social interactions, are also found to be significantly related to trust in automation (Merritt, 2011; Stokes et al., 2010). In a meta-analysis, Hancock et al. (2011) found that factors of team collaboration, such as culture, communication, and shared mental model, influence trust in robots of individuals in a team. These studies indicated that social interaction can be a source for trust calibration. This future direction also corresponds to the recent development of "mesoergonomics" (Karsh, Waterson, & Holden, 2014) where human factors constructs are investigated across different levels. In this case, trust in technology is investigated at both individual level and group/team level.

The results presented in Table 1 answered research question (b1). There was variation in responses from the participants. Also the frequency counts of the factors reported by the participants varied, as seen in Figure. 2 and Fig. 3. Specifically, the frequency counts of usability and competence were significantly higher than the other factors. This is consistent with the prominence-interpretation theory that a variety of elements of the system could be potential antecedents of trust in technology for the users, and some of them are more easily perceived than others (Fogg, 2003; Fogg et al., 2003). In this particular setting, the participants reported that they evaluated the trustworthiness of the technology based on usability, competence, and appearance of the technology, individual characteristics of the user herself/himself, and demand and outcome of the task. Extensive empirical research has been conducted to investigate the factors related to usability and competence (P. Madhavan et al., 2006; Seong & Bisantz, 2008; Yuviler-Gavish & Gopher, 2011). However, more research is needed for some of the other factors, such as demand and outcome of the task (Ezer, Fisk, & Rogers, 2005; Rice & Keller, 2009; Schwark, Dolgov, Graves, & Hor, 2010). These results also showed that qualitative methodology is able to uncover a wide range of factors that can be potentially critical for trust calibration.

The statistical analysis of the relationship between second level factors and trust/distrust evaluation is also consistent with the prominence-interpretation theory. Different elements of the system to be perceived may relate to different evaluations of trust. For example, in this study, appearance of the technology was related to trust but not distrust for passive users. Previous studies found that aesthetics in interface design influence users' trust in online banking systems (Kim & Moon, 1998) and overall perceived credibility of information provided on a website (Robins & Holmes, 2008). In a study of automated navigation systems, Weinstock et al (2012) found that although interface aesthetics were not significantly related to perception of trust, they related to perceived annoyance of the system. It was found that when the automation is perfect, the annoyance rating was lower in the aesthetic condition compared to the non-aesthetic condition. It was possible that aesthetics influenced trust by making the user perceive the automation to be less annoyance, but this effect was not detected due to the ceiling effect, which was a result of the perfectness of the automation.

The statistical analysis aimed to answer research question (b2) and (b3) suggested that, the type of antecedents of trust in technology reported by the users is independent of roles (i.e. active/passive user) and technological/task conditions. However, there should be caution about this result since the frequency counts of some of the factors were very low (even 0 in some cases) thus the analysis may not be reliable. Figure. 3 suggests that the active users reported usability and individual differences as antecedents of trust more frequently than the passive users. Appearance of the technology was only mentioned by passive users. There were also differences in the first level factors between the active users and passive users. In addition, even though some of the responses were assigned the same code, the actual response from the active user and passive user were different. For example, when mentioning the control of the technology, the active users may discuss their own experience with the control device; while the passive users may describe what they think the active users were experiencing: "…yes except the joystick. My partner [had a] problem… control[ling] it within the range."

For research question (c), it is interesting that the mean trust in technology rating did not differ significantly under different antecedents, given that antecedents relates to the binary trust/distrust response significantly. There are two potential causes of this result. First, this could be a result of limited sample size and the unbalanced number of cases of each antecedent. Second, there may be a measurement problem. Under the prominence-interpretation theory, this research assumed that the binary trust/distrust measures the interpretation of a certain antecedent and the trust in technology rating scale measures the overall level of trust in technology. This assumption may not be valid. Future research should develop better instruments to assess a range of trust ratings to measure the constructs in this theory.

4.3. Study 2: physiological compliance and trust (goal 2)

4.3.1. Research questions

This study aimed to understand the process of joint activity, using physiological compliance (PC) measures, in technologically complex environments that include active and passive users. This study also investigated how PC relates to subjective experience of trust.

Hypothesis 1: Task/technology conditions (specifically, task demand and technology reliability) affects the level of group physiological compliance.

Hypothesis 2: Physiological compliance of a group is related to the shared perception about the trustworthiness of the technology among the group members.

4.3.2. Participants

This study recruited participants from students enrolled in an introduction to human factors course in a large, Mid-Western university in the US. The sample size was 48. The participants ranged in age from 19-29 (mean=21.6, SD=1.7). Fifteen of the participants were female (31.3%). The participants received extra course credits for participating in the study. The participants were randomly assigned to two-person groups (n=24) for the experiment. Among the groups, 50% of the participants reported that they did not know the other member in the group, or were only acquainted for a short period of time in the course prior to the experiment; 50% of the participants reported that they knew each other prior to the experiment. In addition, 50% of the groups were mixed-gender groups where the group members had different gender. The two groups who achieved the highest performance were awarded $20 per group member. The protocol of this study was approved by the university's institutional review board (IRB).

4.3.3. Procedure

The general procedure was the same as the description in section 4.1.

Physiology data were collected with a MP150 Data Acquisition System (Biopac Systems Inc.) and Acqknowledge program (version 4.2). The data gathered from the participants included electrodermal activity (EDA) and cardiovascular activity measurements. The EDA measures the changes in the volar surface of the fingers' skin conductance level as well as skin conductance response due to sweat gland (eccrine) activity. Two electrodes were placed on the distal phalanx area of the index and middle finger of the participants to measure EDA. For the active users, the electrodes were placed on the hands that they used for controlling the joystick to minimize intrusiveness of the measurement, since no key pressing was required for the operation of the joystick. Electrocardiogram (ECG) was used for measuring participants' cardiovascular activity. Three electrodes were used for measuring ECG. Two electrodes were placed below the left and right clavicle. The third electrode was placed below the left pectoral muscle. The sample rate was 62.5Hz for EDA and 1000Hz for the ECG. The signals from the two participants in a group were synchronized during data collection.

Low pass filters at 5 Hz were applied to the EDA data to filter high frequency noise in the signals. The EDA signals were resampled at 2Hz before subsequent analysis. Inter-beat-intervals (IBIs) were derived from the ECG. All the derived IBI data were visually examined for artifacts. If an artifact was identified in the IBI series, the corresponding original ECG data would be examined and corrected. The correction would be done by manually removing artificial peaks or recovering R waves. A new IBI data would be derived again after the corrections. All the IBI data were resampled at 2Hz. Data from the same participant were standardized using z-transformation for both EDA and IBI.

Physiological compliance indicators, including signal matching (SM), instantaneous derivative matching (IDM), directional agreement (DA), cross correlation (CC), and weighted coherence (WC) were calculated for the physiology data from each group in the baseline recording (BL) and the three task trials. PC indicators in the time domain, including SM, IDM, DA, and CC, were calculated from the standardized EDA and IBI data. For CC, the lag 0 cross correlation coefficient was used. In addition, CC was calculated directly from the data without detrending or an autocorrelation adjustment. WC was calculated in two steps using R (R Core Team, 2013). First, raw periodograms were derived from the data with fast Fourier transformations after linear trends were removed; and the periodograms were smoothed using modified Daniell smoothers, which are moving averages giving half weight to the end values (Bloomfield, 2000; Cowpertwait & Metcalfe, 2009). A span of 5 was chosen for the smoothers as it provided a good balance of smoothness and resolution. Second, WC scores were calculated by the formula described by Porges et al. (1980) and Henning et al. (2001) in certain frequency ranges. WC of EDA was calculated under the frequency range of about 0.01Hz to 1Hz. WC of IBI was calculated in two different frequency bands: low frequency band (LF, 0.04-0.15Hz) and high frequency band (HF, 0.15-0.4Hz). The high frequency (HF) component of heart rate variability (HRV) is also known as respiratory sinus arrhythmia (RSA) which corresponds to respiratory frequency, and to which parasympathetic nerve system (PNS) activity is a major contributor (Berntson et al., 1997; Task Force of the European Society of Cardiology the North American Society of Pacing and Electrophysiology, 1996). The low frequency (LF) component is affected by both the PNS and the sympathetic nerve system (SNS) (Task Force of the European Society of Cardiology the North American Society of Pacing and Electrophysiology, 1996) and is often used as an index of mental workload (Boucsein & Backs, 2000; De Rivecourt, Kuperus, Post, & Mulder, 2008). Thus WC of IBI was divided into WCLF and WCHF.

4.3.4. Results

The task/technology conditions had significant effects on performance in the tracking task ($F=60.13$, $p<0.001$) and the resource management task ($F=142.32$, $p<0.001$). Specifically, average performance in the tracking task was significantly lower in the hard condition than in the normal condition ($t=9.02$, $p<0.001$); average performance in the resource management task was significantly lower in the low reliability condition than in the normal condition ($t=15.21$, $p<0.001$). No significant effect was found for the task/technology conditions on the performance in the monitoring task. These results are visualized in Figure. 8. WCHF of IBI was the only PC indicator that was significantly affected by the task/technology condition ($F=3.26$, $p=0.049$). Both the hard condition ($t=2.08$, $p=0.044$) and low reliability condition ($t=2.32$, $p=0.025$) had higher average values in WCHF of IBI than in the normal condition.

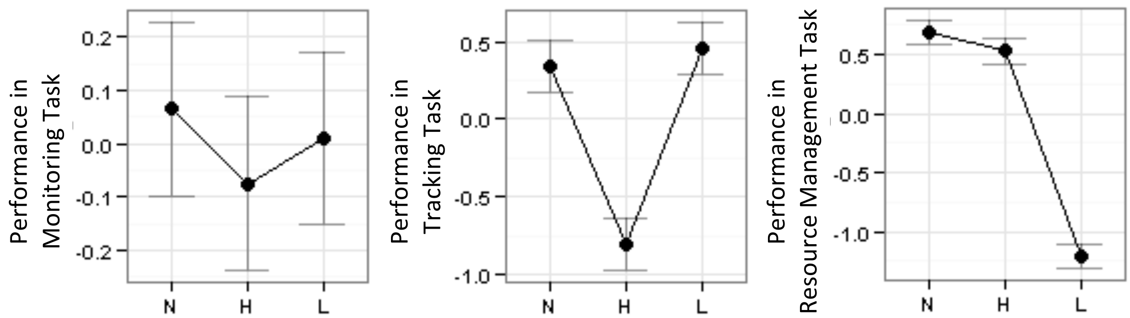

Figure. 8. Mean and standard deviation of the performance in monitoring task, tracking task, and resource management task in the normal condition (N), hard condition (H), and low reliability condition (L).

The task/technology conditions had a significant effect on the average trust in technology rating (F=7.49, p=0.046). Specifically, ratings in the low reliability condition were lower than in the normal condition (t=3.79, p<0.001). A significant effect was also found for workload difference rating (F=4.71, p=0.044). Specifically, difference ratings in the hard condition were lower than in the normal condition (t=2.44, p=0.046). The results are visualized in Figure. 9.

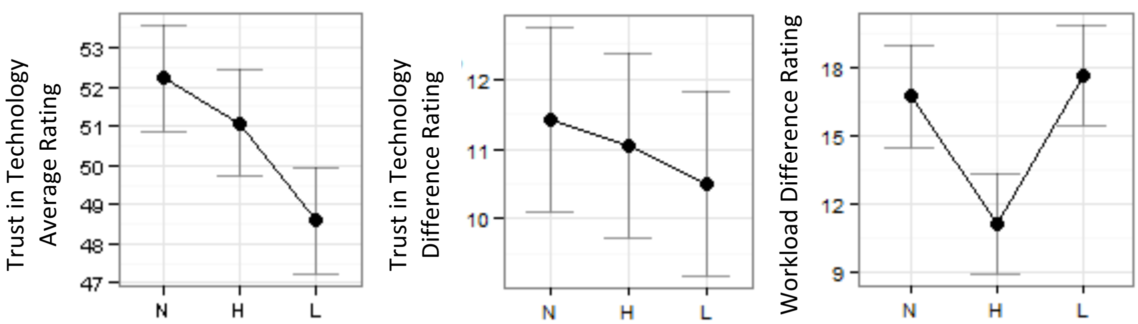

Figure. 9. Mean and standard deviation of subjective ratings, including trust in technology average rating, trust in technology difference rating, and workload difference rating under the normal condition (N), hard condition (H), and low reliability condition (L).

The results also indicated that PC indicators were related to the trust in technology difference rating. Levels of three PC indicators, including DA and CC of EDA and WCHF of IBI, were correlated with values of trust in technology difference rating (for DA of EDA, t=2.11, p=0.014; for CC of EDA, t=1.95, p=0.040; for WCHF of IBI, t=3.24, p=0.008). Higher level of PC as indicated by the three indicators were related lower values of trust in technology difference rating. These results are visualized in Figure. 10.

EDA DA EDA CC

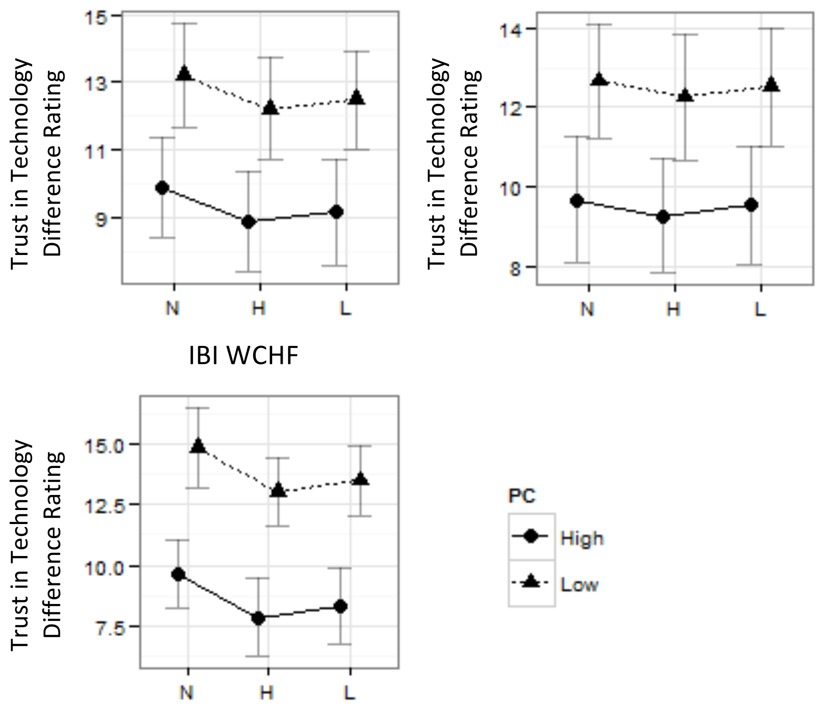

Figure. 10. Mean and standard deviation of the trust in technology difference rating as predicted by different levels of physiological compliance in the normal condition (N), hard condition (H), and low reliability condition (L). +/-1 SD value of the sample were used as high/low level of physiological compliance for data visualization purpose.

4.3.5. Discussion

Hypothesis 1 stated that task/technology conditions will have an effect on PC. The results indicated that only weighted coherence in high frequency (WCHF) in IBI was affected by the task/technology conditions. According to Boucsein and Backs' three arousal model (Boucsein & Backs, 2000), heart rate variability is an indicator of the effort arousal system, which is responsible for inhibiting immediate response behavior to stimuli and allows central processing of information (Backs & Boucsein, 2009; Boucsein, 2012). Thus it is related to operator effort and workload (Aasman, 1987; Roscoe, 1993). Weighted coherence in low frequency (WCLF) and WCHF of IBI could be an indicator of a shared workload level of the two individuals in a group. Other PC indicators with EDA and IBI measures are all related to the affect arousal system, which is responsible for focusing attention and generating orienting response (Backs & Boucsein, 2009; Boucsein, 2012; Boucsein & Backs, 2000). Therefore, the results of this study indicated that under varied task/technology conditions, group members had similar levels of PC on indicators related to attentional and operational control, but different PC levels on indicators related to workload. Specifically, under high demand induced by either the difficulty of the task or the reliability of the technology, the participants had a stronger linkage to the workload to cope with the situation.

Hypothesis 4 states that PC is related to the shared perception of technology trustworthiness among the group members. Support for this hypothesis was found in the difference ratings. Three PC indicators consistently showed that higher PC was related to smaller differences in trust in technology rating between the group members. A previous study found that there is a social influence on trust in technology ratings while the technology is being used in a team setting [10]. This study found that the social influence might be related to how the active user and passive user of the technology interact with each other. Further research is needed for understanding the detailed mechanisms of trust in technology and the trust calibration process at the group level.

4.4. Study 3: user characteristics and trust (goal 3)

4.4.1. Research questions

The purpose of this study was to answer the following two research questions: (1) Do the passive users share perceptions of the technology with the active users? Specifically, do the passive users rate the trustworthiness of the technology the same as the active users? (2) Are team interaction cues related to the passive user's perceptions of the technology and the active user?

4.4.2. Participants

70 participants were recruited from a large mid-western university in the US. Due to a malfunctioning computer during the experiment, the data from four participants were excluded. The participants included were undergraduate students, with 26 students from Engineering and 40 from Consumer Science programs. There were 21 (32%) male participants and 45 (68%) female participants. 12 participants (18%) reported they knew their teammate before the experiment. The participants were paired according to the time slot they requested.

4.4.3. Procedure

The general procedure was the same as the description in section 4.1.

All participants completed the survey measures before coming to the lab for the experiment. The measures included: experience in computer software packages (Hasan, 2003), computer self-efficacy (Compeau & Higgins, 1995), computer anxiety (Heinssen, 1987), propensity to trust technology (Singh, Molloy, & Parasuraman, 1993), and propensity to trust people (Rotter, 1980).

4.4.4. Results

For the active users, the treatment condition results had a significant effect on the trust in technology ratings ($F(2,62) = 8.55$, $p < 0.05$, $\widehat{\omega}^2 = 0.13$). Post hoc comparisons indicated that the ratings in the hard condition were higher than those ratings in the low reliability condition ($F(1,32) = 6.99$, $p < 0.0167$, $\widehat{\omega}^2 = 0.17$); ratings in the normal condition were also higher than those ratings in the low reliability condition ($F(1,32) = 12.34$, $p < 0.0167$, $\widehat{\omega}^2 = 0.27$). Similar results were found for the passive users. For the treatment condition results showed a significant effect on the trust in the technology ($F(2,62) = 12.42$, $p < 0.05$, $\widehat{\omega}^2 = 0.34$). The mean ratings for both hard ($F(1,32) = 7.56$, $p < 0.0167$, $\widehat{\omega}^2 = 0.18$) and low reliability ($F(1,32) = 22.53$, $p < 0.0167$, $\widehat{\omega}^2 = 0.42$) were lower than the ratings in the normal condition. Although the passive user results had a higher mean rating than the active user results for all the conditions. The differences were not statistically significant. This finding implies that the active users and the passive users shared similar perceptions towards the technology across the treatment conditions. Figure. 11 shows that the means and 95% confidence intervals for the trust in the technology rating under each condition for both the active and the passive users. There was no significant effect between the treatment conditions and the treatment positions for all three categories in the trust for team ratings in both the active users and in the passive users. Also, there was no significant difference found when we compared the active users with the passive users.

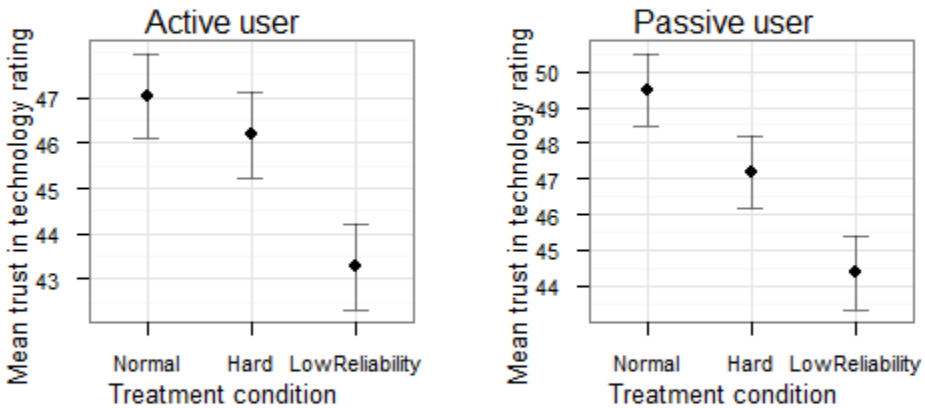

Figure. 11. Means and 95% confidence intervals for trust in technology rating under the condition normal, hard, and low reliability for the active users and passive users.

Different patterns resulted about the importance predictors of trust in the technology ratings for the active and the passive users. This was showed in an exploratory data analysis, where several variables were selected as predictors to explore the factors that affected participants' ratings for trust in the technology. The predictors included the independent variables (treatment conditions (CON) and treatment temporal positions (POS)),demographic variables and interaction variables. Demographic variables included: computer experience (CE), computer self-efficacy (CSE), computer anxiety (CA), propensity to trust technology (PTT), propensity to trust people (PTP), gender of active user (AGEN), gender of the passive user (PGEN), familiarity between the active user and passive user (FAM), education major of the participant (engineering or non-engineering; MAJR).Interaction variables included: performance in the monitoring task (PM), performance in the tracking task (PT), performance in the resource management task (PR) and communication (COM). These variables are summarized in table 1. The trust in the technology ratings for the first time two participants worked together and the subsequent interactions may have been affected by different mechanisms. Separate analysis was done to address this issue of analysis for the "between-subject" part of the data which was the first time the two participants in a pair worked together, and the analysis for the "within-subject" part of the data which included the subsequent interactions.

The model selection procedure used for the exploratory data analysis consisted of three steps guided by the information-theoretic approach (Anderson & Burnham, 2002). First, to predict the outcome variables we used a linear model to the fitted data. This was done by fitting an additive general linear model to the "between-subject" part of the data, and an addictive linear mixed-effects model, with random intercept, to the "within-subject" part of the data. Then models with all possible combinations of the given predictors were fitted to the data. The third step was the AIC value and Akaike weights which we calculated for all the models and a set of best models were selected as candidate models. The model which had the lowest AIC value was selected as the reference, and all the models which had a AIC value of less than 2 deviation of the reference model were also selected (Burnham & Anderson, 2001).Due to the small sample size in this study, all AIC values were substituted by AICc values (Burnham & Anderson, 2001). The goal of identifying the variables that strongly influenced the outcome, the importance and average coefficient of the variables was accessed from all the candidate models. The importance of the variables was determined by calculating the sum of Akaike weights for the candidate models that contained a specific variable. Then the variables were ranked by their sum. The average coefficient was the average of the regression coefficients from the candidate models being weighted using the Akaike weights (Burnham & Anderson, 1998).Confidence intervals for the regression coefficient estimates were also calculated in the model averaging process. All the analyses were conducted using R (R Development Core Team, 2011) with the Lme4 package (Bates, Maechler, & Bolker, 2011) and MuMIn (Barton, 2010) package software.

For the active users, 6 candidate models were selected for the "in between part" data and 12 candidate models were selected for the "within part" data. Table 2 shows the relative variable importance and the sign of the average coefficient for each variable. In both cases, the gender of the active user was one of the most important variables for predicting trust in the technology rating; specifically, males tended to give higher ratings of trust. The computer anxiety level scores negatively correlate to the trusting in the technology rating in the "in between part" data. The test results showed that the correlation coefficient for the active user's gender and the computer anxiety level was 0.055 which was not significant. In the "within part" data, the treatment conditions (especially the low reliability condition) strongly affected the trust in the technology ratings.

Table 2. Relative variable importance and sign of average coefficient of the predictor variables for active user's trust in technology.

"Between part"			**"Within part"**		
Variable	Relative importance	Sign of the average coefficient	Variable	Relative importance	Sign of the average coefficient
CA	1.00	-	CON	1.00	- (low reliability)
AGEN	1.00	+ (male)	AGEN	1.00	+ (male)
PR	0.58		PGEN	0.88	
PTT	0.31		MAJR	0.87	
PT	0.14		CA	0.51	
CSE	0.13		POS	0.31	
			FAM	0.29	

Note. The value in sign of the average coefficient is omitted if the 95% confidence interval of the coefficient covers zero.

For passive users' trust in the technology ratings, the number of candidate models were 12 and 11 for the "in between part" and "within part" data respectively. Different patterns were found for the relative importance of predictor variables for the two sets of datum (see Table 3). Communication and performance levels for the tracking task were the most important variables used to predict the trust in the technology in the "in between part" data. The more the two participants in a team talked to each other, the lower the passive user rated the trust in the technology. The higher level of the performance in the tracking task, the higher the passive user rated the trust in the technology. For the "within part" data, the treatment condition was the only variable that had a significant impact on the passive user's trust in the technology rating as both the hard and low reliability condition harmed the rating scores.

Table 3. Relative variable importance and sign of average coefficient of the predictor variables for passive user's trust in technology.

"Between part"			**"Within part"**		
Variable	Relative importance	Sign of the average coefficient	Variable	Relative importance	Sign of the average coefficient
COM	1.00	-	CON	1.00	- (hard)
PT	1.00	+			- (lowreliability)
PR	0.52		MAJR	1.00	
CA	0.27		PGEN	0.94	
CSE	0.26		PM	0.93	
PTT	0.20		AGEN	0.93	
AGEN	0.07		FAM	0.34	
MAJR	0.07		PTT	0.19	
PM	0.06		CSE	0.17	
			POS	0.15	

Note. The value in sign of the average coefficient is omitted if the 95% confidence interval of the coefficient covers zero.

4.4.5. Discussion

Although confirmatory data analysis indicated that groups shared the perception of trust in the technology for the three treatment conditions, exploratory data analysis showed that there may be different mechanisms for the users to build-up those perceptions. In experiment 2, the individual differences (specifically, computer anxiety and gender results) strongly affected the active user's perception about trust in the technology. This finding is consistent with the previous studies where the terms of the effect of individual differences on trust in the technology for active users was evaluated. Merritt and Ilgen (2008) demonstrated that the propensity to trust significantly affects the initial trust to the machine and also confirms the relationship between the machine characteristics and a history-based trust level. A recent study (Poornima Madhavan & Phillips, 2010) found that computer self-efficacy rates significantly moderates the effect of the system reliability on the system trust. Computer anxiety is a concept that relates to computer avoidance (Chua, Chen, & Wong, 1999; Jones, 2010), which may be linked to trust in computer technologies. Survey studies found that computer anxiety is negatively related to perceived ease of use (Brown, 2002) and perceived usefulness (Igbaria & Iivari, 1995) of a technology which are predictable for actual usage of technology. A recent research (Tung, Chang, & Chou, 2008) demonstrated that trust in technology is closely related to both perceived ease of use and perceived ease of use. These researches imply that computer anxiety may also relate to trust in technology. This study confirmed this relationship. Previous research (Markert, 1996) did not found trust in technology to be differentiated by gender. The contradict finding in this study may due to the unbalanced number of females and males. However, more research should be conducted to investigate the relationship between gender and trust in technology.

However, a different pattern was observed for the passive user. Interaction variables (i.e. communication, performance in the tracking task, and performance in the resource management task) were at the top of the list relative to predicting the passive user's trust in the technology for the first interaction. The interaction process seemed to serve as the trust calibration purpose for the passive users. Passive users calibrated their trust in the technology level by observing and participating in the interaction process, and finally achieved a shared trust level with the active user. One may argue that this is also a result of different expertise levels between the active users and passive users. The active users received hands-on training, while the passive users did not. However, further evidence indicated the relative variable importance list from the "within part" data showed that the most important variables to predict the passive user's trust in the technology rating were a mixture of demographic variables and interaction variables. None of interaction variables appeared on the active user's list. This suggests that the interaction process remained important for the passive users' trust calibration. Intervention to optimize the trust level for the passive user should take into consideration the three-way interaction of the technology, the active user, and the passive user at the same time.

No significant difference was found in the trust level in the team measurement across the three treatment conditions. This may imply that the trust level in team measurement is less likely related to the functioning of the technology than other contextual or team related factors. Future research should explore this measurement using various strategies to facilitate or restrict the factors known to contribute to teamwork such as communication skills.

4.5. Study 4: affective process and trust (goal 4)

4.5.1. Research questions

In the scenario where an individual operator interacts with a technology, both incidental affect and integral affect may influence trust (see Figure. 12). Incidental affect is the affective state of an individual before the interaction and integral affect is the affective state of an individual during the interaction (Kugler, Connolly, & Ordóñez, 2012). These two constructs were rarely distinguished in the research of affect in trust in technology. In the context of team and trust in technology, differentiating the effects of these two kinds of affect and understanding their mechanism of influencing trust is particularly important. In Barsade and Gibson's group affect framework (1998), incidental affect is part of the affective context of the system and it may be influenced by factors such as group composition, organizational culture, and physical environment. During the task process, integral affect changes dynamically as the individuals' affective states were influenced by the task, their interaction with the technology, and the explicit and implicit affective transfer processes among individuals (Barsade & Gibson, 2012).

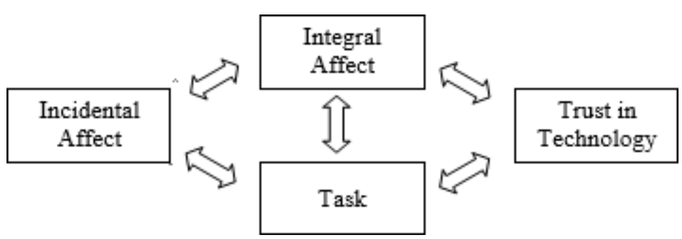

Figure. 12. The relationship among incidental affect, integral affect, task, and trust in technology.

The purpose of the current study is to investigate the influence of incidental affect and integral affect on trust in technology in teams. The participants in this study worked in two-person teams which consisted of an active user and a passive user (Montague & Xu, 2012) and worked on a multi-tasking computerized environment with varied technology reliability levels and task demand levels.

Incidental affect was manipulated through mood induction by having participants' individually view affective images (Bradley & Lang, 2007). Technology and task conditions were manipulated to examine how integral affect changed under different task processes. Affective scale was used to measure individuals' affective state at the end of the task and this measure was used as an indication of integral affect.

4.5.2. Participants

Fifty four volunteer participants were recruited from a large mid-western university in the US. The participants were grouped into two-person teams (n=27) for the experiment. The average age was 22.31 (SD=5.42, ranged 18 to 56). Thirty four (63%) of the participants were female. Fourteen partici-pants (26%) reported that they never met their teammates before the study.

4.5.3. Procedure

The general procedure was the same as the description in section 4.1.

A total number of 90 affective images were selected from the International Affective Picture System (IAPS) (Bradley & Lang, 2007). The 90 images were grouped into positive, neutral, and negative with 30 images in each group. The 30 images in each group were further broken down into 3 10-image sets. Pilot study showed that positive image sets increased participants' positive affect and negative image sets increased participants' negative affect. These affective images were used to manipulate initial mood. This variable included three conditions: positive, neutral, and negative. The participants individually view a set of affective images before each task session.

The Positive and Negative Affect Schedule (PANAS) (Tellegen, Watson, & Clark, 1988) was used for measuring positive affect and negative affect. The trust in technology scaled developed by Jian et al. (2000) were used for measuring trust in technology.

4.5.4. Results

To test the effects of initial mood and technological/task conditions on positive affect (or negative affect) after the task, LME models were fitted to the data with initial mood, technological/task conditions, negative affect (or positive affect), role (active/passive user), and all possible two-way interaction terms as predictors.

The results indicated that initial mood had a significant effect on negative effect ($F(2, 97.11)=3.87$, $p<0.05$); see Figure 13. Specifically, negative initial mood condition resulted an significantly higher negative affect than the average of positive initial mood condition and neutral mood condition ($F(1, 23.26)=7.18$, $p<0.05$). However, initial mood did not have a significant effect on positive affect ($F(1, 25.52)=0.87$, $p=0.43$).

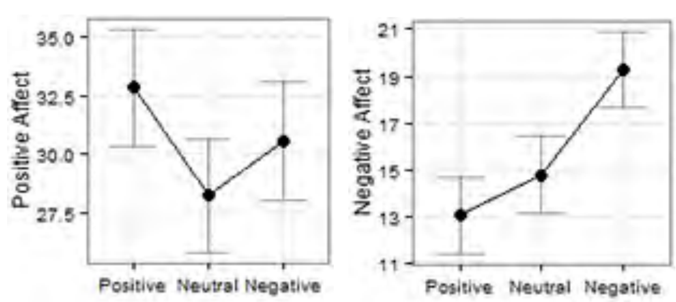

Figure. 13. The mean and standard error of the predicted values of integral affect (positive and negative) on positive, neutral, and negative initial mood conditions.

Technological/task conditions had significant effects on both positive affect (F(2, 97.11)=3.00, p<0.05) and negative affect (F(2, 95.59)=3.36, p<0.05); see Figure 14. Further tests showed that low reliability condition resulted a significantly lower positive affect than the average of normal condition and difficult condition (F(1, 94.62)=4.17, p<0.05). Difficult condition resulted a significantly higher negative affect than the average of normal condition and low reliability condition (F(1, 94.83)=5.55, p<0.05).

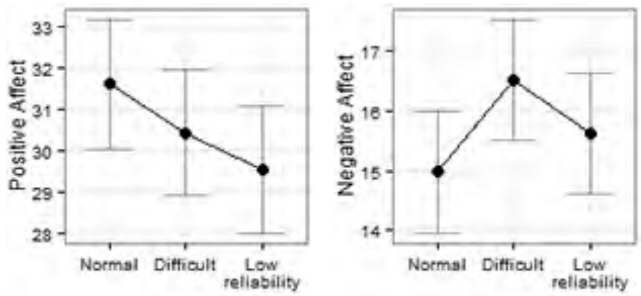

Figure. 14. The mean and standard error of the predicted values of integral affect (positive and negative) on normal, difficult, and low reliability technological/task conditions.

LME model was fitted to the data using positive affect, negative affect, initial mood, technological/task conditions, role, and all possible two-way interaction terms to predict trust in technology. The results indicated that positive affect had a significant positve main effect on trust in technology when all the other variables were centered (F(1, 106.39)=9.61, p<0.05). Furthermore, positive affect moderated the relationship between initial mood and trust in technology through a significant interation effect (F(2, 107.99)=5.76, p<0.05); see Figure. 15. Specifically, high level of positive affect resulted a higher level of trust in technology in positive and neutral intial mood conditions comparing to negative initial mood condition.

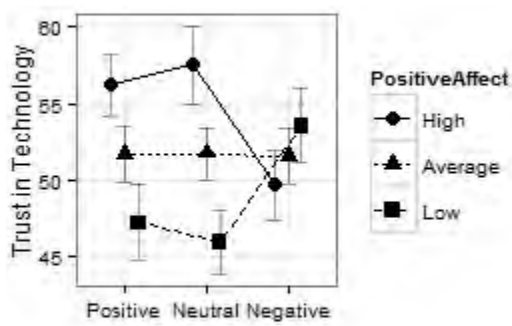

Figure. 15. The mean and standard error of the predicted values of trust in technology on positive, neutral, and negative initial mood conditions and on different levels of positive affect. High and low levels positive affect were defined as +1 SD and -1 SD of the mean.

Technological/task conditions had significant effects on trust in technology (F(2, 94.83)=10.30, p<0.05); see Figure. 16. Specifically, low reliability condition resulted a significantly lower trust in technology level than the average of normal condition and difficult condition (F(1, 93.72)=18.18, p<0.05).

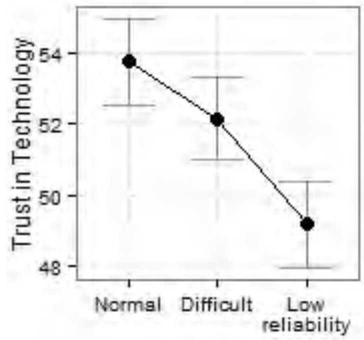

Figure. 16. The mean and standard error of the predicted values of trust in technology on normal, difficult, and low reliability technological/task conditions.

Mediation analysis was conducted to test the mediation effect of positive affect on the relationship between technological/task conditions and trust in technology (see Figure. 17) following the bootstrapping approach (MacKinnon, 2007; Preacher & Hayes, 2004). The calculations of bias-corrected bootstrap confidence intervals (CIs) indicated that the relative indirect effect is significant that low reliability condition led to lower level of positive affect which in turn related to lower level of trust in technology (ab=-0.05; 95% CI: -0.13, -0.01).

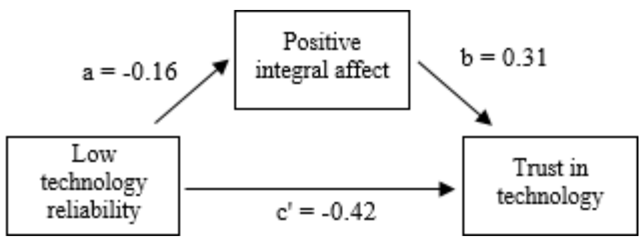

Figure. 17. The mediation model of technological/task conditions, positive integral affect, and trust in technology. The independent variable was coded as low reliability condition compares to the mean of normal and difficult condition. a, b, and c' were standardized coefficients.

4.5.5. Discussion

The positive correlation between positive integral affect and trust in technology found in this study was consistent with previous findings with individual task performers (Merritt, 2011; Stokes et al., 2010). This study showed that the correlation still holds significance under teamwork context. However, negative integral affect was not found to be related trust in technology. Given that negative affect was found to be related to interpersonal trust (Dunn & Schweitzer, 2005; Ferrin, Bligh, & Kohles, 2007), more study is need to understand if this is a difference between technological trust and interpersonal trust.

The significant mediation effect of positive integral affect on technological/task condition and trust in technology showed role of affect in the trust calibration process. Note that in the mediation analysis, both the direct effect and the indirect effect were significant. This indicated that affect is only part of the trust calibration mechanism. However, there was a limitation in this study that it was difficult to accurately estimate the effect size of indirect effect in relation to the total effect due to the complex design.

An important limitation in this study was that integral affect was measured at the end of the task. Although this measure still provided important information about integral affect, especially at the moment when the participants were asked to evaluate their trust in technology, it did not take the whole task process into account. One obstacle was the measurement of affect during the task process that the survey instrument was intrusive to the task process. Recent development in physiological measure of affect could be a potential solution. For example, facial expression recognition technology could be used to measure the individual's affective state continuously (Littlewort et al., 2011). This is useful for understanding how emotions are generated during the interaction and transferred among individuals in a team.

This study found an interesting pattern that it seems negative incidental affect neutralized the relationship between positive integral affect and trust in technology. According to the affective infusion model (Forgas, 1995), an individual is more likely to use heuristic processing strategy when in a positive affective state, and the level of positive affect may be used as a piece of information that is considered to be relevant to the judgement task at hand (Clore et al., 2001). In this case, one could observe a positive correlation between positive affect and level of trust. On the other hand, an individual is more likely to use substantive processing strategy when in a negative affective state. In this case, positive and negative affect may still influence decision and judgement that affective states could have a priming effect on information processing, such as attention, perception, memory retrieval, and decision selection (Niedenthal, Krauth-Gruber, & Ric, 2006). However, since the individual is using more information to form the decision or judgement, the effect of affective state may be smaller than that in the heuristic processing route. In this study, the negative incidental affect could have made the participants more likely to use the substantive processing route when calibrating trust thus the effect of positive integral affect was reduced under this condition.

Many previous studies have found that incidental affect could influence trust (e.g., Stokes et al., 2010) and the use of technology could induce affect (e.g., Swangnetr, Zhu, Taylor, & Kaber, 2010). This study showed that both incidental affect and integral affect have effects on trust in technology. These have new implication for the design of systems that facilitate calibration for appropriate trust in technology. For example, to improve initial trust when a technology is first introduced, one could induce positive mood as incidental affect to facilitate the formation of higher level of trust (Merritt, 2011). At the same time, the use of appropriate emotional design, such as interfaces with humanoid features (Swangnetr et al., 2010), could induce positive integral affect to improve trust. Design features that facilitate positive interaction among team members may also promote trust in technology. Another point to note is that negative incidental affect might not be always a bad thing for trust calibration. As the results suggested, it might cause the users more likely to use substantive process strategy for trust calibration thus reducing the effect of "unwanted" integral affect on trust calibration. For example, this could help prevent over-trust caused by high level of positive affect when the task happened to be easier than usual when the technology is first introduced.

5. Publications related to the project

[1] **Xu, J.**, Montague, E., Gratch, J., Hancock, P., Jeon, M., & Pfaff, M. (2015). Advances of Research in Affective Processes in Communication and Collaboration. *Proceedings of the 59th Annual Meeting of Human Factors and Ergonomics Society.*

[2] **Xu, J.**, Montague, E. (2015). Affect and Trust in Technology in Teams: the Effect of Incidental Affect and Integral Affect. *Proceedings of the 59th Annual Meeting of Human Factors and Ergonomics Society.*

[3] **Xu, J.**, Le, K., Deitermann, A., & Montague, E. (2014). How different types of users develop trust in technology: A qualitative analysis of the antecedents of active and passive user trust in a shared technology. *Applied Ergonomics, 45*(6), 1495-1503.

[4] Montague, E., **Xu, J.**, & Chiou, E. (2014). Shared Experiences of Technology and Trust: An Experimental Study of Physiological Compliance between Active and Passive Users in Technology Mediated Collaborative Encounters. *IEEE Transactions on Human-Machine Systems, 44*(5), 614-624.

[5] **Xu, J.**, Montague, E. (2013). Group polarization of trust in technology. *Proceedings of the 57th Annual Meeting of Human Factors and Ergonomics Society, 56*(1), 344-348.

[6] **Xu, J.**, Montague, E., (2013) Working with an Invisible Active User: Understanding Trust in Technology and Co-User from the Perspective of a Passive User. *Interacting with Computers, 25*(5), 375-385.

[7] **Xu, J.**, & Montague, E. (2012). Psychophysiology of the passive user: Exploring the effect of technological conditions and personality traits. *International Journal of Industrial Ergonomics, 42*(5), 505-512.

[8] Montague, E., & **Xu, J.** (2012). Understanding active and passive users: The effects of an active user using normal, hard and unreliable technologies on user assessment of trust in technology and co-user. *Applied Ergonomics, 43*(4), 702-712.

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1.

1. Report Type

Final Report

Primary Contact E-mail

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Primary Contact Phone Number

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3125036400

Organization / Institution name

Northwestern University

Grant/Contract Title

The full title of the funded effort.

Active and Passive User Trust in Sociotechnical Systems

Grant/Contract Number

AFOSR assigned control number. It must begin with "FA9550" or "F49620" or "FA2386".

FA9550-12-1-0311

Principal Investigator Name

The full name of the principal investigator on the grant or contract.

Enid Montague

Program Manager

The AFOSR Program Manager currently assigned to the award

Benjamin A Knott, PhD

Reporting Period Start Date

06/30/2012

Reporting Period End Date

06/30/2015

Abstract

Active and passive user is a way to understand how users can have different perspectives of the use of technologies in complex socio-technical systems. These different perspectives can influence how trust is formed and calibrated for individual users and teams of users. As a result, appropriate use, misuse, disuse, or abuse of technology may occur. This project pioneered the research in active passive user systems through a series of experimental studies. The goals of the project were to understand: (1) pair-level factors that shape trust, (2) psychophysiological markers that predict trust, (3) user characteristics that relate to trust, and (4) the affective process of trust.

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Archival Publications (published) during reporting period:

[1] Xu, J., Montague, E., Gratch, J., Hancock, P., Jeon, M., & Pfaff, M. (2015). Advances of Research in Affective Processes in Communication and Collaboration. Proceedings of the 59th Annual Meeting of Human Factors and Ergonomics Society.
[2] Xu, J., Montague, E. (2015). Affect and Trust in Technology in Teams: the Effect of Incidental Affect and Integral Affect. Proceedings of the 59th Annual Meeting of Human Factors and Ergonomics Society.
[3] Xu, J., Le, K., Deitermann, A., & Montague, E. (2014). How different types of users develop trust in technology: A qualitative analysis of the antecedents of active and passive user trust in a shared technology. Applied Ergonomics, 45(6), 1495-1503.
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[5] Xu, J., Montague, E. (2013). Group polarization of trust in technology. Proceedings of the 57th Annual Meeting of Human Factors and Ergonomics Society, 56(1), 344-348.
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Changes in research objectives (if any):

Added a study regarding the role of affect.

Change in AFOSR Program Manager, if any:

Extensions granted or milestones slipped, if any:

AFOSR LRIR Number

LRIR Title

Reporting Period

Laboratory Task Manager

Program Officer

Research Objectives

Technical Summary

Funding Summary by Cost Category (by FY, $K)

	Starting FY	FY+1	FY+2
Salary			
Equipment/Facilities			
Supplies			
Total			

Report Document

Report Document - Text Analysis

Report Document - Text Analysis

Appendix Documents

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