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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

Enid Montague*, Jie Xu

Department of Industrial and Systems Engineering, University of Wisconsin – Madison, 3017 Mechanical Engineering, 1513 University Avenue, Madison, WI 53706, USA

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ABSTRACT

The aim of this study was to understand how passive users perceive the trustworthiness of active users and technologies under varying technological conditions. An experimental study was designed to vary the functioning of technologies that active users interacted with, while passive users observed these interactions. Active and passive user ratings of technology and partner were collected. Exploratory data analysis suggests that passive users developed perceptions of technologies based on the functioning of the technology and how the active user interacted with the technology. Findings from this research have implications for the design of technologies in environments where active and passive users interact with technologies in different ways. Future work in this area should explore interventions that lead to enhanced affective engagement and trust calibration.

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1. Introduction

1.1. Active user versus passive user

1.1.1. The “activeness” dimension

In many human–computer interaction models an individual user interacts with a technology. In these models, users are divided into “active process operators” and “passive process operators” (Johansson, 1989; Persson et al., 2001). According to Persson et al.’s (2001) definition, an active process operator’s work is distinguished from the passive process operator’s work by the predominance of monitoring tasks. If most of the tasks are monitoring tasks, rather than tasks such a prediction, planning, control, etc., then the work could be considered passive process operator’s work. This dichotomization of users has a continuous underlying dimension of “activeness”. The “activeness” of a user is a result of task allocation between the user and the technology. The level of control changes as different levels of automated technology are introduced into the work environment, from purely manual control to a fully automated process (Endsley and Kiris, 1995). The research literature suggests that passive process operators, in highly automated environments, may encounter several potential problems, including slower problem detection, loss of situation awareness, and loss of skill (Wickens et al., 2004).

The “activeness” dimension in user-technology interaction can be applied to complex socio-technical systems. In work system models, the system is comprised of people, technology, tasks, the organization, and the environment (Smith and Carayon-Sainfort, 1989). Individuals in the environment can have different roles or perspectives of the system. For example, some users may have specialized knowledge or experiences with a technology, while others have limited knowledge and no experience. Users may also take on the roles of service providers or customers with varying levels of power within a system. For example, an x-ray technician has specialized knowledge about the x-ray technology. Their training includes knowledge about the inner workings of the technology and they may use the technologies many times a day. Physicians also interact with the x-ray machines, but they interact with the technologies differently; for example, they are more likely to use the technology to communicate with patients and other care providers. Finally, patients may develop opinions about the machines used to provide care to them, and are often concerned with the machine results. i.e., “do I have an abnormality or not”.

One method of characterizing different users is to introduce the concept of “incidental user” (Inbar and Tractinsky, 2009), which

Abbreviations: MATB, multi attribute task battery; CE, computer experience; CSE, computer self-efficacy; CA, computer anxiety; PTT, propensity to trust technology; PTP, propensity to trust people; RT, reaction time; RMSE, root mean square error.

* Corresponding author. Tel.: +1 608 890 3546; fax: +1 608 262 8454.
E-mail address: emontague@wisc.edu (E. Montague).

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relates to the "activeness" dimension of technology usage. An incidental user is interested in the information output presented by the technology, but has little or no control over the technology. The user's communication with the technology is mediated by another user referred to as an "active user" who has control over the technology (Inbar and Tractinsky, 2009). In this paper, the term "active user" and "passive user" are defined as opposite cases on a continuous dimension of "activeness" in cooperative work. Passive users do not have full control of the technology, while active users have enough control to operate the technology. A passive user will be similar to a passive process operator in his/her relationship with the technology being used. However, the passive user may be faced with less monotony than the passive process operator, since sometimes the passive user can "control" the technology indirectly by communicating with the active user.

A general framework for cooperative work involves both an active user and a passive user of the technology (Fig. 1). The three-way interaction using the technology is among the active user, the passive user and the technology illustrated in a work systems framework. The interaction process is directed by certain goals. For example, in the healthcare context, the care provider's and patient's primary goal is to treat the patient's disease or illness. Other goals may include reducing pain or preventing future illnesses. These goals are achieved by accomplishing the tasks. Tasks may include information exchange between the doctor and the patient, diagnosis of the disease, and developing a treatment plan. Various technologies may be used to complete tasks including electronic health records, patient monitoring devices, and decision aids. Finally, the outcomes of this interaction process will generate feedback for participants.

1.1.2. Passive users in the real world

Passive users are prevalent in the real world. A thorough discussion of passive users in face-to-face customer service encounters is discussed in Inbar and Tractinsky (2010). Some other examples of areas where passive users are important include aviation, education, and healthcare. In the cockpits of commercial airplanes, the captain and the first officer will alternate roles between Pilot Flying (PF) and the Pilot Not Flying (PNF). The PNF could be considered a passive user who takes a supportive role and attends to duties such as communicating with the air traffic controller and monitoring instruments (Hutchins, 1995). Monitoring instruments is an important duty for the PNF, and is associated with a high percentage of aviation safety problems (Sumwalt et al., 2002). Research indicates that the PNF is less likely to lose situational awareness than the PF. Thus, the captain of the aircraft should consider taking the role of the PNF in an emergency situation (Jentsch et al., 1999).

In educational environments, students can be passive users if teachers are sole operators of the technology. For example, research shows that although interactive whiteboards are versatile and effective tools for teaching, student access is limited (Hall and Higgins, 2005). In other cases, technologies such as socialized computers, designed to facilitate collaborative learning, have advantages over individual learning techniques (Mori et al., 2009). Some students may take the role of a passive user when activities require taking turns to interact with the technology (Inkpen et al., 1997) or access to the technology is limited (Pal et al., 2006).

In healthcare, the patient is often a passive user. They receive information or treatment from health technologies operated by the clinician, who is the active user. Previous research indicates that doctor–patient interaction is important in influencing health outcomes (Pearson and Raeke, 2000). In healthcare, technologies and computer use can function as moderators in the doctor–patient interaction (Kaplan et al., 1989; Woolley et al., 1978). In primary care offices, researchers have investigated the effects of computer use on patient outcomes. The results indicate that the physician's computer skill can significantly affect patients' ratings of satisfaction with the care they receive (Garrison et al., 2002). To improve interactions, researchers have proposed that patient perspectives should be considered when designing system improvements (Delbanco, 1992) and for risk management (Itoh et al., 2006).

In the cases mentioned above, passive users are at least as important as active users. For this reason, passive users should be treated as important stakeholders in the design process. Incorporating design features for passive users, including sharing information with the passive user and increasing the passive user's degree of control over the technology, can optimize trust and effectiveness, thus improving satisfaction of the customers (passive users) in face-to-face service encounters (Inbar and Tractinsky, 2011). However, technologies are typically only designed for active users, such as operators, administrators, or technicians, rather than for passive users (Inbar and Tractinsky, 2009). When designing technologies to be used by active and passive users, some design requirements for active users can also be applied to passive users. For example, good data visualization can help the passive user understand the current state of the technology. However, situations involving three-way interactions that include the technology, the active user, and the passive user, are complicated and more research is needed to inform design requirements. For example, in healthcare, differences in expertise and past experience

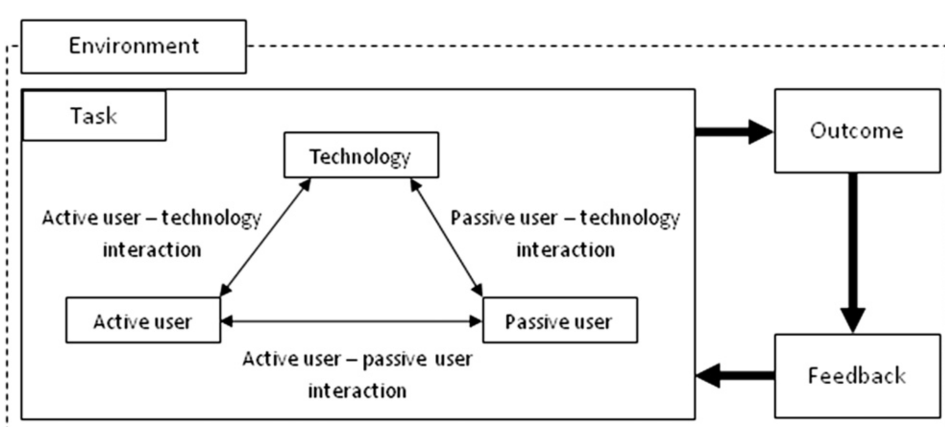

Fig. 1. A general conceptual model of a system involving a passive user.

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may affect the interaction between different types of users and technologies and therefore influence the outcome. Without specifically considering active and passive user needs in the design, it is not possible to ensure that all user needs have been met.

1.2. Passive user's perception about the system

1.2.1. Shared perceptions between the active user and the passive user

In some interactions with active and passive users, achieving a shared understanding and trust in the shared technologies is critical to the interpersonal relationship and system outcomes. In other systems, shared understandings may be less important. Inbar and Tractinsky (2009) describe a common grocery store checkout process as an illustration of designs that engage both active and passive users. In the checkout line, cashiers scan groceries and both cashiers and customers can see the price on their display. Often times, there is a separate, smaller display for customers that shows the price of an item. This display serves several functions: 1) it reduces uncertainty for the customer, so that they can ensure the cashier is charging them the correct amount and 2) it provides an opportunity to involve both the customer and the cashier in troubleshooting if discrepancies arise. Some technologies in healthcare settings are designed to facilitate shared understanding between patients and care providers. One example is an ultrasound to monitor the progression of a pregnancy (Montague, 2009; Inbar and Tractinsky, 2009). Here, the environment is usually designed to create an interaction between the patient and the technology to facilitate a specific user experience, i.e., bonding with the fetus. Some design elements include screens that are placed at patient's eye-level. Some procedural elements might be a technician or care provider who explains what the patient is seeing on the screen. For example, many providers will say, "here is the heart beat". In other settings, the environment might not be designed to facilitate a shared perspective. In these cases the patient may not have a full perspective of the technology functions or outputs. For example, a patient connected to a heart rate monitor might not be able to physically see the display. The care provider might not explain the interface elements or the alarms, leaving the patient to make potentially biased or erroneous decisions about the technology's functioning.

In cases where the passive user has limited access to information, it is important to design technologies that facilitate appropriate perceptions of the technologies and appropriate perceptions of the active users. The outcomes of the three-way interaction affect the patient, the health provider operating the medical technology, and the patient's understanding of the technology (Montague, 2010). This leads to several important questions about the use of the technology with active and passive users. First, how are active and passive users' impressions of shared technology formed, maintained and changed when they interact with technologies with active or passive users?

1.2.2. Interpersonal trust and trust in technology

In a socio-technical system, trust is considered a fundamental aspect of interpersonal relationships (Tschannen-Moran and Hoy, 2000) and of relationships with technologies (Lee and Moray, 1994). Research shows that in the team context, trust is influenced by the quality of communication, satisfaction, and performance (Costa and Anderson, 2011). Different levels of trust in technology can also influence whether the technology is used appropriately, rejected, used in a way it wasn't designed for, or over-used (Parasuraman and Riley, 1997).

Research suggests there are similarities and differences in the development of interpersonal trust and trust in the technology. Some people tend to apply social conventions to the technologies, while interacting with the technology (Reeves and Nass, 1996), and similarities can be observed for trust in human-to-human and human-to-technology relationships. On the other hand, some argue that there are considerable differences in these two types of trust. Lewandowsky et al. (2000) found that trust and self-confidence could predict participants' reliance on the technology. In the trust development model proposed by Madhavan and Wiegmann (2007), humans may use sequential process to assess trust in both human-to-human trust and human-to-technology trust; humans consider other humans and technologies different in terms of dispositional features. e.g., humans are adaptable and technology is invariant, and response tendencies, e.g., the humans are imperfect and technology is perfect. However, few studies have investigated whether these findings remain consistent in situations where multiple users with varied perspectives interact with a technology.

1.3. Research questions

The study described in this manuscript investigated the three-way interaction between a technology, an active user, and a passive user. The research questions were:

- Does the presence of the passive user affect the active user's behavior and perception of the technology?
- Do passive users develop a shared perception of the technology with the active users? Specifically, do passive users provide ratings of trust in the technology similar to those provided by active users?
- Are team interaction behaviors related to the passive user's perceptions of the technology and the active user?

2. Method

2.1. Experiment 1: individual use of technology

The purpose of experiment 1 was to understand the performance of active users, without passive users present. This was the baseline for exploring the effect of having a passive user observe an active user's interactions with the technologies. The hypothesis in this experiment was that the active user's performance would be altered by different conditions, including task difficulty and technology reliability. It is also hypothesized that different conditions would alter the active user's perception of the technology.

2.1.1. Participants

15 volunteers participated in the experiment. All participants were recruited from a large mid-western university community in the United States. Nine of the participants were students majoring in consumer science, and six participants were engineering students. Among the participants, seven were male and eight were female. All participants received extra credit in a course for participating in the experiment.

2.1.2. Equipment and tasks

The Multi Attribute Task Battery (MATB) program (Comstock and Arnegard, 1992) was used to simulate the task and the program being used (see Fig. 2). The task consisted of three subtasks: monitoring, tracking, and resource management. The monitoring task required the participants to respond to lights and fluctuation of dials as quickly as possible. The tracking task required the participants to keep a steadily moving target in the center of the screen using a mouse. The resource management task required the participants to control several pumps to maintain optimum liquid level in two tanks.

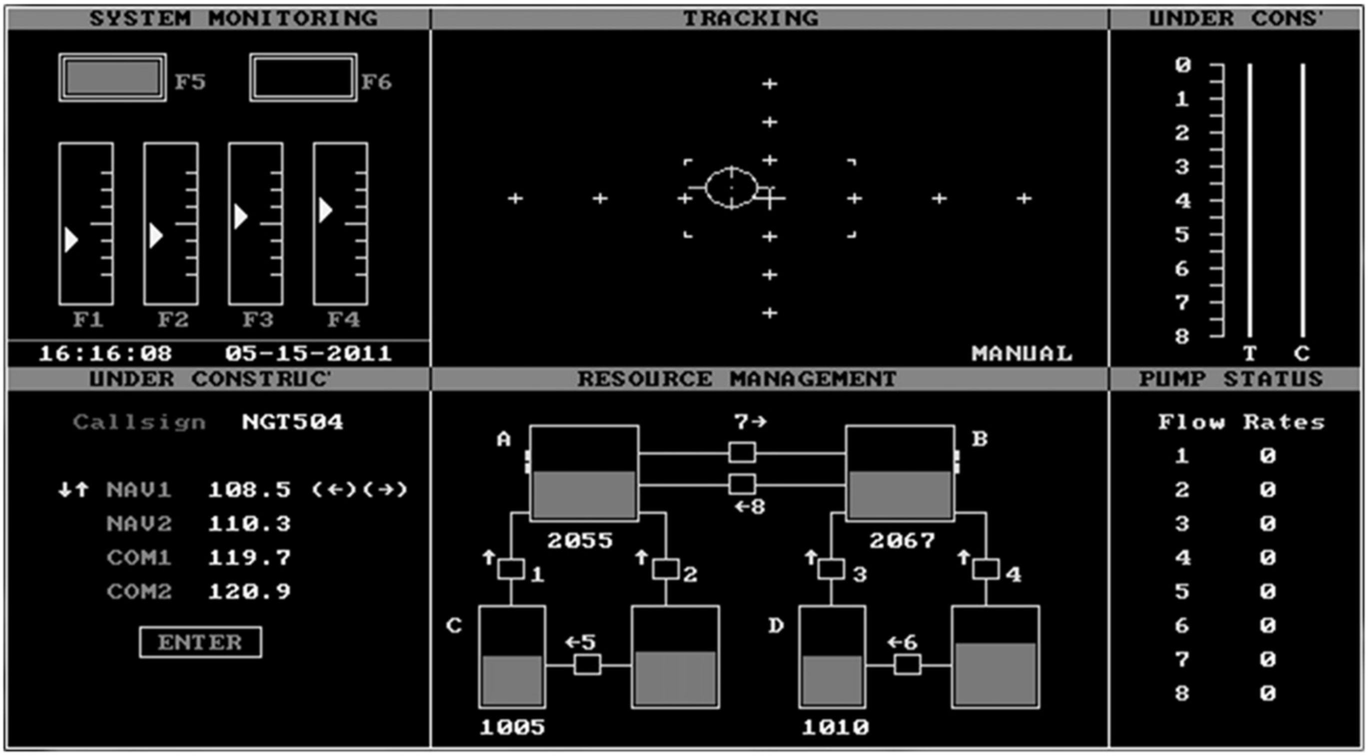

Fig. 2. The interface of the Multi Attribute Task Battery (MATB).

2.1.3. Design

The experiment used a counterbalanced within subjects design, with one independent variable. Three conditions were represented in the variable with three different contexts of the technology state: normal condition, hard condition, and low reliability condition. 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 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. The participants completed three trials (each trial lasted 6 min) for the three conditions.

2.1.4. Procedure and measurements

Upon arrival, participants were asked to complete an informed consent form. They were then asked to read through an instruction sheet about the MATB. Oral instructions about the MATB were also given to make sure the participants fully understood what to do during the experiment. Finally, participants went through a 6 min hands-on training session for MATB, with the same difficulty and reliability found in the normal condition.

Participants completed monitoring, tracking, and resource management sub-tasks for each condition. The sequences of the three conditions were counterbalanced across participants. The trust in technology (Jian et al., 2000) scale was administered after each condition. Participants' performance was scored for each task, including reaction time (RT) in the monitoring task, root mean square error (RMSE) in the tracking task, and error scores in the resource management task.

2.1.5. Data analysis

In the confirmatory data analysis, a repeated measures ANOVA was used to test the relationship between the treatment condition and the outcome variables (trust in technology and performance on the three tasks). To test for a practice/fatigue effect, the temporal position of the treatment condition was considered in the analysis. If the test results showed significant effects, post-hoc pair-wise comparisons were conducted using Bonferroni correction (family-wise critical p-value is 0.0167 for a 0.05 α level). Logarithm transformations were applied to the performance measures since the normality assumption was violated. The statistical analysis program R (R Development Core Team, 2011) was used for all analyses.

2.1.6. Results

Means and standard deviations of the dependent measures in experiment 1 are presented in Table 2.

For the monitoring task no significant effect was found for RT. Treatment had a significant effect on root mean square error of the tracking task ($F\,(2, 26) = 34.13$, $p < 0.05$, $\hat{\omega}^2 = 0.60$) and an error score in the resource management task ($F\,(2, 26) = 32.67$, $p < 0.05$, $\hat{\omega}^2 = 0.58$). For the tracking task, the participants performed better for both normal ($F\,(1, 14) = 50.65$, $p < 0.0167$, $\hat{\omega}^2 = 0.62$) and low reliability ($F\,(1, 14) = 41.44$, $p < 0.0167$, $\hat{\omega}^2 = 0.57$) conditions, compared to hard conditions. For the resource management task, participants performed worse in the low reliability conditions, compared to normal ($F\,(1, 14) = 34.58$, $p < 0.0167$, $\hat{\omega}^2 = 0.53$) and hard conditions ($F\,(1, 14) = 65.68$, $p < 0.0167$, $\hat{\omega}^2 = 0.68$).

Trust in technology ratings showed a significant differences among the treatment conditions ($F\,(2, 26) = 7.16$, $p < 0.05$, $\hat{\omega}^2 = 0.21$). The ratings for low reliability conditions ($F\,(1, 14) = 17.06$, $p < 0.0167$, $\hat{\omega}^2 = 0.35$) were significantly lower than for normal conditions.

Fig. 3 shows the significant relationships. These findings support the expectation that treatment conditions affected the active user's performance and perception, which was a required assumption for the experiment 2 protocol.

2.2. Experiment 2: team use of the technology

The primary purpose of experiment 2 was to examine whether the presence of a passive user affected the active user's performance. The second purpose was to understand active and passive user perceptions of each other across technological conditions.

2.2.1. Participants

70 new participants were recruited from the same research participant pool as experiment 1. Due to a malfunctioning computer during the experiment, the data from four participants were excluded. All participants were undergraduate students, 26 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. Participants were paired according to the time slot they requested and were randomly assigned to the active or passive user role.

2.2.2. Equipment, tasks, and design

The equipment, task, and design remained the same as in experiment 1. During the task, the passive user was not allowed to control the computer, but the two participants could communicate freely.

2.2.3. Procedure and measurements

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

Upon arrival, participants were introduced to each other by their first name. Individually, they were asked to complete informed consent forms. In the training section that followed, active and passive users received different levels of training with the MATB. Active users received paper and oral instruction about the MATB, as well as a 6-minute hands-on training with the MATB. Passive users only received paper and oral instruction.

Participants were asked to work as a team and to try to maintain high performance in all tasks. A trust in team instrument (Costa and Anderson, 2011) in addition to the same instrument used in experiment 1 to measure trust in technology were administered to the participants individually after each trial. Communication between the active and passive users was measured by the proportion of time participants talked to each other out of the total task length time.

2.2.4. Data analysis

The data analysis for experiment 2 consisted of two phases. The first phase, called confirmatory data analysis, tested the effects of the treatment conditions on the outcome variables. To compare the passive users with the active users in trust in team and trust in technology, tests were conducted using a difference score, which

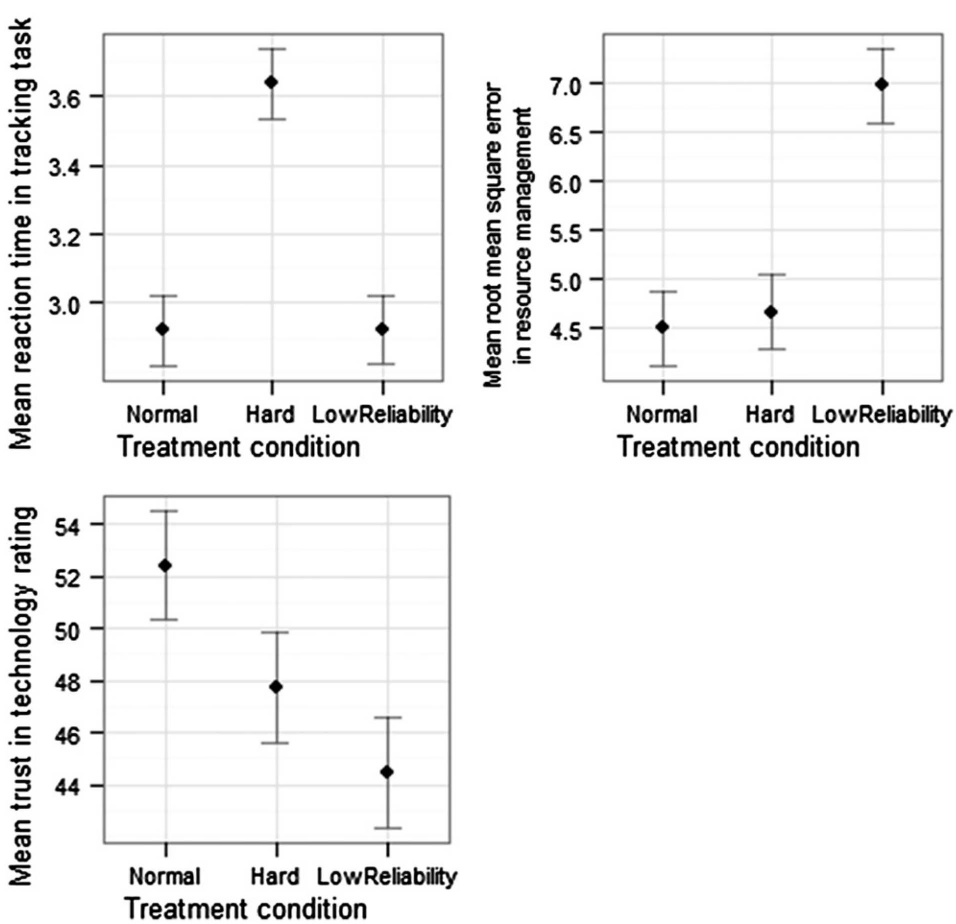

Fig. 3. Means and 95% confidence intervals of the significant relationships in experiment 1. Please note that high performance score means low performance.

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was calculated by subtracting the active users' rating from the passive users' rating.

The second phase was called 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), and 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. Because the trust in the technology ratings for the first interaction may have affected subsequent interactions, separate analyses were conducted to address this issue called "between subjects" and "with-in subjects". The "between-subjects" part of the data was the first time the two participants in a pair worked together, and the "within-subjects" part of the data included subsequent interactions.

The model selection procedure used for the exploratory data analysis consisted of three steps guided by the information-theoretic approach (Anderson and Burnham, 2002). First, to predict the outcome variables a linear model was applied to the fitted data. This was done by fitting an additive general linear model to the between-subjects part of the data, and an additive 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 calculating the AIC value and Akaike weights for all the models and selecting a set of best models as candidate models. The model which had the lowest AIC value was selected as the reference, and all the models which had an AIC value of less than 2 deviations of the reference model were also selected (Burnham and Anderson, 2001). Due to the small sample size in this study, all AIC values were substituted by AICc values (Burnham and Anderson, 2001). Candidate models provided insight into which variables influenced the outcome, and the importance and average coefficient of the variables. 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 weighted using the Akaike calculation (Burnham and Anderson, 1998). Confidence intervals for the regression coefficient estimates were also calculated in the model averaging process. All analyses were conducted using R (R Development Core Team, 2011) with the Lme4 (Bates et al., 2011) and MuMIn (Barton, 2010) packages.

Table 1
Variables used in the exploratory data analysis and their definitions.

Independent variables
Treatment conditions (TC)
• *Normal/hard/low reliability.*
Treatment temporal positions (POS)
• *First trial/second trail/third trail.*
Demographic variables
Computer experience (CE)
• *One's experience in difference computer packages.*
Computer self-efficacy (CSE)
• *One's judgment of the capability of using a computer.*
Computer anxiety(CA)
• *One's feeling of anxiety towards computer use.*
Propensity to trust technology (PTT)
• *One's general tendency to trust technology.*
Propensity to trust people (PTP)
• *One's general tendency to trust people.*
Gender of active user (AGEN)
Gender of the passive user (PGEN)
Familiarity (FAM)
• *Participants' responses about whether they know their partner.*
Major of the participant (MAJR)
• *Engineering/non-engineering.*
Interaction variables
Performance in the monitoring task (PM)
• *Measured by reaction time.*
Performance in the tracking task (PT)
• *Measured by root mean square error.*
Performance in the resource management task (PR)
• *Measured by absolute deviation from the optimal liquid level.*
Communication (COM)
• *Measured by percentage of the time the two participants talked to each other.*

2.2.5. Results of the confirmatory data analysis

Means and standard deviations of the dependent measures for both participant groups in experiment two are presented in Table 2.

A temporal position effect was found in reaction time for the monitoring task ($F\,(2,62) = 6.95$, $p < 0.05$, $\hat{\omega}^2 = 0.21$). Among the positions (first, second or third), performance in position three was significantly better than in position one ($F\,(1,32) = 11.33$, $p < 0.0167$, $\hat{\omega}^2 = 0.26$). Performance on the tracking task was significantly affected by the treatment condition, i.e., normal, low reliability, or hard, ($F\,(2,62) = 27.27$, $p < 0.05$, $\hat{\omega}^2 = 0.54$). Performance in the hard condition was poorer than in both the normal condition ($F\,(1,32) = 37.01$, $p < 0.0167$, $\hat{\omega}^2 = 0.26$) and the low reliability condition ($F\,(1,32) = 29.74$, $p < 0.0167$, $\hat{\omega}^2 = 0.49$). Also, performance on the resource management task was significantly affected by the treatment condition ($F\,(2,62) = 51.82$, $p < 0.05$, $\hat{\omega}^2 = 0.69$). Better average performance was found in normal condition ($F\,(1,32) = 133.05$, $p < 0.0167$, $\hat{\omega}^2 = 0.81$) and hard condition ($F\,(1,32) = 70.36$, $p < 0.0167$, $\hat{\omega}^2 = 0.70$) comparing to low reliability condition.

The treatment conditions did not show a significant effect on the communication measure. However, the temporal position effect was significant ($F\,(2,62) = 11.89$, $p < 0.05$, $\hat{\omega}^2 = 0.33$) as the mean communication time length was longer in position one than in position two ($F\,(1,32) = 30.78$, $p < 0.0167$, $\hat{\omega}^2 = 0.50$) and in position three ($F\,(1,32) = 10.77$, $p < 0.0167$, $\hat{\omega}^2 = 0.25$). Performance results in the monitoring task improved across trials and teams were able to achieve higher performance results with less communication. This may imply that, on average, teamwork improved over time.

Fig. 4 shows the treatment effect on performance in the tracking task and in the resource management task. Fig. 5 shows the position effect on communication and performance results in the monitoring task.

For active users, treatment condition significantly affected trust in technology ratings ($F\,(2,62) = 8.55$, $p < 0.05$, $\hat{\omega}^2 = 0.13$). Post hoc comparisons indicated that ratings in the hard condition were higher than ratings in the low reliability condition ($F\,(1,32) = 6.99$, $p < 0.0167$, $\hat{\omega}^2 = 0.17$); ratings in the normal condition were also higher than ratings in the low reliability condition ($F\,(1,32) = 12.34$, $p < 0.0167$, $\hat{\omega}^2 = 0.27$). Similar results were found for passive users. For the treatment condition, a significant effect was found between treatment condition and trust in the technology ($F\,(2,62) = 12.42$, $p < 0.05$, $\hat{\omega}^2 = 0.34$). The mean ratings of the conditions, hard ($F\,(1,32) = 7.56$, $p < 0.0167$, $\hat{\omega}^2 = 0.18$) and low reliability ($F\,(1,32) = 22.53$, $p < 0.0167$, $\hat{\omega}^2 = 0.42$) were lower than ratings in the normal condition. Although passive users reported a higher mean

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Table 2
Means and standard deviations of the dependent variables under different treatment conditions for experiment 1 and experiment 2.

	Experiment 1			Experiment 2: active users			Experiment 2: passive users		
	Normal	Hard	Low reliability	Normal	Hard	Low reliability	Normal	Hard	Low reliability
RT in monitoring task	4.8 (1.4)	5.4 (1.0)	5.8 (2.1)	4.5 (1.7)	4.5 (1.5)	5.2 (1.9)	–	–	–
RMSE in tracking task	20.7 (11.1)	**42.3 (21.2)**	19.7 (7.2)	21.0 (20.5)	**33.1 (23.9)**	24.8 (26.9)	–	–	–
Error scores in resource management task	236.0 (304.9)	252.6 (323.4)	**1250.6 (642.1)**	284.0 (323.1)	257.5 (336.7)	**1306.3 (662.5)**	–	–	–
Trust in technology	52.4 (5.0)	47.7 (7.7)	**44.5 (7.9)**	47.0 (8.1)	46.2 (8.4)	**43.3 (7.8)**	49.5 (7.7)	**47.2 (8.2)**	**44.4 (7.6)**
Trust in team –perceived trustworthiness	–	–	–	24.8 (2.9)	24.5 (3.3)	24.9 (3.2)	23.9 (3.2)	23.7 (2.7)	23.5 (3.2)
Trust in team –cooperative behaviors	–	–	–	23.8 (2.9)	23.8 (3.2)	23.7 (3.2)	23.3 (2.4)	23.3 (2.3)	23.0 (2.1)
Trust in team –monitoring behaviors	–	–	–	10.3 (2.7)	10.4 (3.1)	10.5 (2.9)	9.8 (2.6)	10.2 (2.1)	9.6 (2.8)

Note. The value in hard condition and low reliability condition are in bold if significantly ($p < 0.05$) different from normal condition.

rating of trust in technology than active users for all conditions, the differences were not statistically significant. This finding implies that the active users and the passive users shared similar perceptions of the technology across the treatment conditions. Fig. 6 shows means and 95% confidence intervals for the trust in the technology ratings under each condition for both the active and the passive users.

No significant effects were found between treatment conditions and treatment positions for all three categories in the trust for team ratings for active and passive users. Finally, no significant difference was found when active users were compared to passive users.

2.2.6. *Results of the exploratory data analysis*

Candidate models were created to describe predictors of trust in technology for active and passive users. For the active users, six candidate models were selected for the between subjects data and 12 candidate models were selected for the within subjects data. Table 3 shows the selected models and corresponding AICc, delta (AICc of that model minus the lowest AICc from all possible models) and Akaike weight value. Table 4 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. Scores on the computer anxiety measure negatively correlated with trust in technology ratings in the between subjects data. The correlation coefficient for the active user's gender and the computer anxiety was not significant at 0.055. In the within subjects data, the treatment condition, especially the low reliability condition, affected trust in the technology ratings.

For passive users' trust in the technology ratings, the number of candidate models were 12 and 11 for the between subjects and within subjects data respectively (see Table 5). Different patterns were found for the relative importance of predictor variables for the between subjects and within subjects (see Table 6). Communication and performance on the tracking task were the most important variables to predict trust in technology in the between subjects data. Increased communication by participants in a team lowered the passive user rated trust in the technology. Higher performances in the tracking task were related to higher ratings of trust in technology from the passive user. For the within subjects data, the treatment condition was the only variable having a significant impact on the passive user's trust in the technology, as both the hard and low reliability conditions influenced the rating scores.

2.2.7. *Comparing experiment 2 with experiment 1*

Among the three sub-tasks, passive users were most involved in the monitoring task. This task required continuous monitoring and active users tended to ask passive users for help in this task. Passive users had moderate involvement in the resource management task and strategies for controlling the pumps. Passive users had minimal involvement in the tracking task since this task was continuously controlled by active users. However, the presence of a passive user did affect the active user performance in the monitoring task, such that the temporal position affected the performance in the monitoring task for the active users, but not the individual users; though

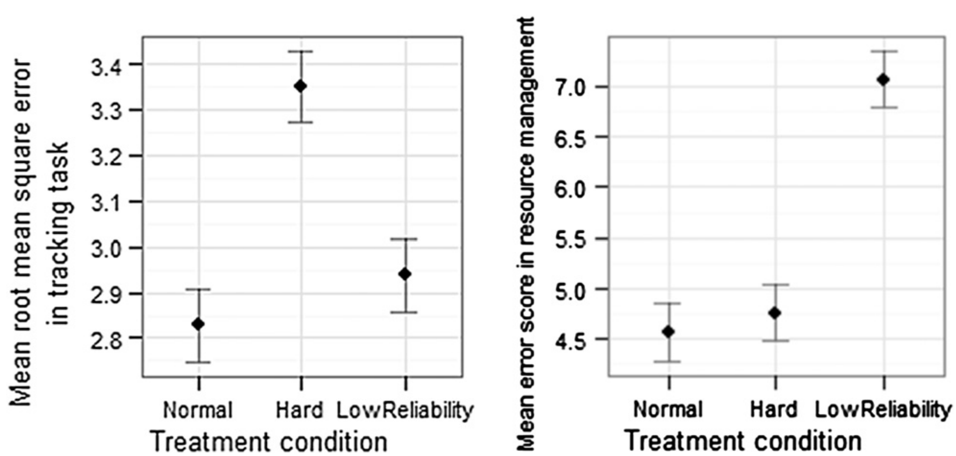

Fig. 4. Means and 95% confidence intervals for performance in tracking task and performance in resource management task under each treatment condition. Please note that high performance score means low performance.

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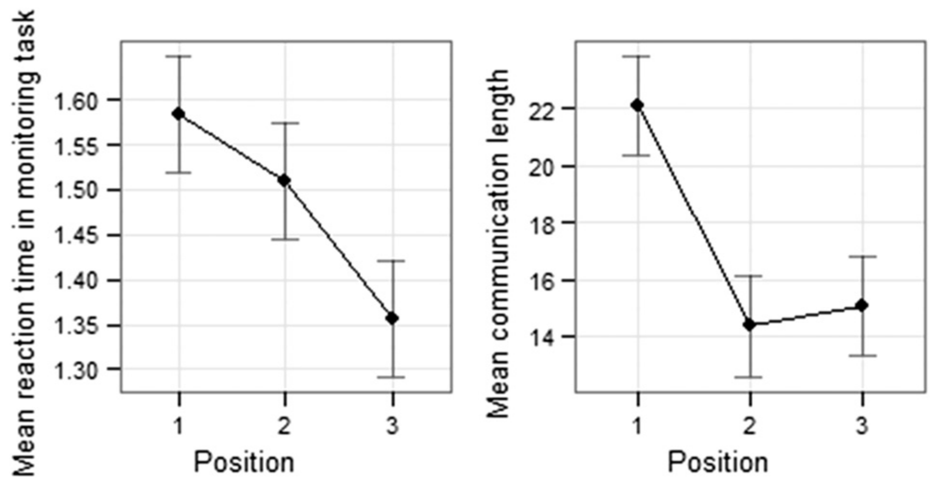

Fig. 5. Means and 95% confidence intervals for performance in monitoring task and communication length under each position. Please note that high performance score means low performance.

the difference between average performance levels in those two groups was not statistically significant. The presence of a passive user did not affect the active user performance in the remaining sub-tasks in which they had a lower involvement.

The presence of a passive user also affected active users' trust in the technology. The active users' mean ratings score for trust in the technology was lower than the individual user levels in all three treatment conditions, although, the only differences in between performance in the normal condition were statistically significant ($F\,(1,46) = 7.27$, $p < 0.05$, $\hat{\omega}^2 = 0.09$).

3. Discussion

3.1. The effect of the presence of a passive user

The presence of a passive user effected the active user's performance level depending upon the passive user's involvement in the specific task. The active users' performance in sub-tasks where passive users' involvement was minimal, i.e., tracking task and resource management task, remained identical to individual user performance levels. Trust in technology ratings from active users were lower when a passive user was present, compared to individual users of the same technology. These findings may indicate a social influence on ratings of trust in technologies, when technologies are used in multi-user setting. However, the effect of social influence on trust calibration, i.e., whether the user's perceived trust in the technology corresponds to the capability of the technology (Lee and See, 2004), remains unknown in this study. Future research should investigate this effect and develop guidelines for designing technologies to adjust trust levels for active users to ensure their trust level is appropriate. Future research should also explore the effects of context and mismatched goals between active and passive users on design requirements.

3.2. Active user and passive user's perception of the system

Although confirmatory data analyses indicate 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 by which users develop these perceptions. In experiment 2, individual differences (specifically, computer anxiety and gender) influenced the active user's perception of trust in the technology. This finding is consistent with previous studies that found relationships between individual differences and ratings of trust in technology for active users. Merritt and Ilgen (2008) demonstrated that a user's propensity to trust significantly affects his/her initial trust to technology. Another study found that a person's self-efficacy with computers moderates the effects of system reliability on system trust (Madhavan and Phillips, 2010). Computer anxiety is a concept that relates to

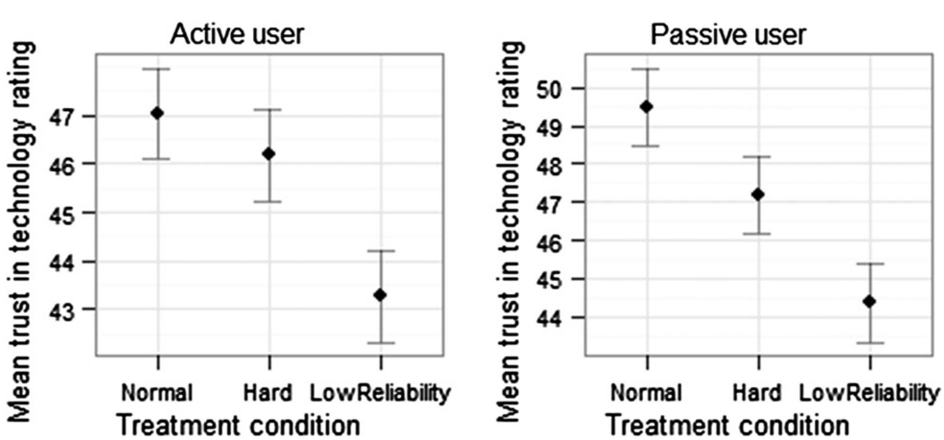

Fig. 6. Means and 95% confidence intervals for trust in technology rating under the condition normal, hard, and low reliability for the active users and passive users.

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Table 3
Models selected for active user's trust in technology and the corresponding AICc, delta, and Akaike weight value for each model.

Candidate Models	AICc	Delta	Akaike Weight
Models for the "between part"			
CA + AGEN + PR	87.94	0	0.28
CA + AGEN + PR + PTT	88.95	1.01	0.17
CA + AGEN	89.14	1.20	0.15
CA + AGEN + PR + PT	89.31	1.36	0.14
CA + AGEN + PTT	89.32	1.37	0.14
CA + AGEN + PR +CSE	89.53	1.59	0.13
Models for the "within part"			
CON + AGEN + PGEN + MAJR + CA	613.96	0	0.14
CON + AGEN + PGEN + MAJR	614.09	0.13	0.13
CON + AGEN + PGEN + MAJR + CA + POS	614.73	0.77	0.1
CON + AGEN + PGEN + MAJR + POS	614.74	0.78	0.09
CON + AGEN + PGEN + MAJR + FAM	614.89	0.93	0.09
CON + AGEN + PGEN + MAJR + CA + FAM	614.90	0.94	0.09
CON + AGEN + PGEN + CA	615.44	1.48	0.07
CON + AGEN + MAJR + CA	615.54	1.58	0.06
CON + AGEN + PGEN	615.58	1.62	0.06
CON + AGEN + PGEN + MAJR + POS + FAM	615.66	1.70	0.06
CON + AGEN + PGEN + MAJR + CA + POS + FAM	615.78	1.82	0.06
CON + AGEN +MAJR	615.81	1.85	0.06

computer avoidance (Chua et al., 1999; Jones, 2010), which also may be linked to trust in computers and other technologies. Survey studies found that computer anxiety is negatively related to perceived ease of use (Brown, 2002) and perceived usefulness (Igbaria and Iivari, 1995) of a technology which are related to outcomes such as technology usage. Another study demonstrated that trust in technology is closely related to both perceived ease of use and behavioral intention to use of technology (Tung et al., 2008). Findings from these studies imply that the construct computer anxiety may also influence a user's trust in a technology. The study described in this manuscript provided support for this relationship. Previous studies have not found trust in technology to be influenced by gender (Markert, 1996). The multi-user perspective may account for the different findings. These findings may also be the result of the unbalanced number of female and male participants. More research should be conducted to investigate the relationship between gender and trust in technology, particularly in team settings.

Passive users may use a different mechanism to evaluate trust in a technology. In this study, different variables influenced passive user ratings of trust in the technology. Interaction variables, i.e., communication, performance in the tracking task, and performance in the resource management task, were the strongest

Table 4
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.

Table 5
Models selected for passive user's trust in technology and the corresponding AICc, delta, and Akaike weight value for each model.

Candidate Models	AICc	Delta	Akaike Weight
Models for the "between part"			
COM + PT	230.20	0	0.15
COM + PT + PR + PTT	230.36	0.17	0.14
COM + PT + PR	230.63	0.43	0.12
COM + PT + PR + CA + CSE	231.51	1.31	0.08
COM + PT + PR + CA	231.74	1.54	0.07
COM + PT + AGEN	231.76	1.56	0.07
COM + PT + MAJR	231.79	1.59	0.07
COM + PT +CSE	231.85	1.65	0.07
COM + PT + CA	231.89	1.69	0.06
COM + PT + PTT	231.93	1.74	0.06
COM + PT + PR + CA + CSE + PM	231.97	1.78	0.06
COM + PT + PR + CSE	232.11	1.92	0.06
Models for the "within part"			
CON + MAJR + PGEN + PM + AGEN	627.92	0	0.17
CON + MAJR + PGEN + PM + AGEN + FAM	628.44	0.52	0.13
CON + MAJR + PGEN + PM + AGEN + PTT	628.75	0.83	0.11
CON + MAJR + PGEN + PM + AGEN +CSE	629.04	1.12	0.09
CON + MAJR + PGEN + PM + AGEN + POS	629.27	1.35	0.08
CON + MAJR + PGEN + PM + AGEN + FAM + PTT	629.39	1.47	0.08
CON + MAJR + PGEN + PM + AGEN + FAM +CSE	629.47	1.55	0.08
CON + MAJR + PGEN + PM	629.57	1.65	0.07
CON + MAJR + PGEN + AGEN	629.67	1.75	0.07
CON + MAJR + PM + AGEN	629.84	1.92	0.06
CON + MAJR + PGEN + PM + AGEN + FAM + POS	629.91	1.99	0.06

predictors of the passive user's trust in the technology in the first interaction. The interaction process seemed to serve as a calibrator of trust for passive users, as passive users assessed trust by observing and participating in the interaction process, and then developing a perception of trust in the technology that was shared with the active user.

Active users received hands-on training, while passive users did not. In the within data analyses, the most important predictors of passive users' trust in the technology were a mixture of demographic and interaction variables. None of interaction variables influenced active users' ratings of trust. This suggests that the interaction process remained important for trust calibration by passive users, but not by active users. Interventions to optimize the trust level for the passive user should take into consideration the three-way interaction between the technology, the active user, and the passive user.

No significant differences were found in measures of trust in teammate across the three treatment conditions. This may imply

Table 6
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	+			– (low reliability)
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.

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that the trust in teammate measure is not influenced by the functioning of the technology and is possibly influenced by other contextual or team related factors. Future research should explore measures of team cohesiveness in multi-user team settings using strategies that facilitate or restrict the factors known to contribute to team outcomes such as communication.

3.3. Limitations

The first study limitation was the experimental approach to investigate the teams. As discussed by Henning et al. (2009), the teams in this experiment lacked a long-term working relationships, team commitment, and goals. In work settings, active and passive users may have both long and short-term relationships. In patient–clinician relationships, for example, patients and providers can have long term, e.g., primary care, chronic disease management, or short-term, relationships e.g., urgent care, emergency care. Though this study focuses on the latter, it is important to evaluate both types of relationships.

The results from the exploratory data analysis should remain exploratory. Examining the set of models consisting of all the possible combinations of variables can increase the risk of overfitting the model to the data (Anderson and Burnham, 2002) such that random error is described as a significant relationship. In this study, this risk was reduced by limiting the results and discussion to the most important predictor variables. Also, because the sample size was relatively small, interactions between variables were not examined. Future studies should explore the effects of the variables with a larger sample size and confirm the causal relationships of the variables with additional experiments.

4. Conclusion

Passive users play an important role as consumers and teammates. As technology–mediated collaborative encounters increase in prevalence, it is important to understand how to design new technologies for both active and passive users. This study found that (1) the presence of a passive user altered the active user's performance and perception of trust in technology; and (2) in trust calibration between active and passive users, dispositional factors, e.g., computer anxiety, are important for the active users, while interactions between the active user and the passive user, and between the active user and the technology may be more influential for passive users. These findings have implications for system design. In the design of technologies for active users, social influence from the passive users should be considered, particularly when designing to optimize appropriate trust and reliance on technologies. Finally, the system should facilitate communication between active and passive users, and support the situation awareness of passive users, to help passive users appropriately calibrate their trust in the technology.

This study provided some insight into variables that contribute to passive user ratings of trust in technologies and trust in their teammates who interact with the technologies. These variables should be explored in future studies to better understand how to design the technology for passive users and in field studies to understand the role of context in active and passive user assessment and use of technologies. For example, patients are sometimes passive users. Their perceptions of technologies used in their care can influence when and how these technologies are used. Their assessments of their provider's skill with technologies and as care providers are also important to achieving health and safety outcomes. However, patients and providers represent a unique type of team. Patients and the providers might not always see themselves as members of a team. These contextual elements may vary across health domains, e.g., primary care versus surgery, and particular health systems. Alternatively, in other domains, technology mediation may not be defined as a service relationship and may instead be defined as individuals in a team working together. In these cases, it may be important to understand which functions should be allocated to active and passive users to reduce complacency and increase team performance outcomes. It may also be important to understand the correct amount of training and information required for both the active and passive users. Finally, it is important to better understand the passive user perceptions of the technology in service applications, such as brief encounters with shared interfaces in everyday activities as grocery shopping, in addition to interactions that occur over time.

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