Effects of Human–Machine Competition on Intent Errors in a Target Detection Task

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Abstract

Objective: This investigation examined the impact of human–machine competition (John Henry effects) on intent errors. John Henry effects, expressed as an unwilling- ness to use automation, were hypothesized to increase as a function of operators' personal investment in unaided performance. Background: Misuse and disuse often occur because operators (a) cannot determine if automation or a nonautomated alternative maximizes the likelihood of task success (appraisal errors) or (b) know the utilities of the options but disregard this information when deciding to use or not to use automation (intent errors). Although appraisal errors have been extensively studied, there is a paucity of information regarding the causes and prevention of intent errors. Methods: Operators were told how many errors they and an automated device made on a target detection task. Self-reliant operators (high personal investment) could depend on their performance or automation to identify a target. Other-reliant operators (low personal investment) could rely on another person or automation. Results: As predicted, self-reliance increased dis-use and decreased misuse. Conclusion: When the disuse and misuse data are viewed together, they strongly support the supposition that personal investment in unaided performance affects the likelihood of John Henry effects and intent errors. Application: These results demonstrate the need for a model of operator decision making that takes into account intent as well as appraisal errors. Potential applications include developing interventions to counter the deleterious effects of human–machine competition and intent errors on automation usage decisions.

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Effects of Human–Machine Competition on Intent Errors in a Target Detection Task

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Objective: This investigation examined the impact of human–machine competition (John Henry effects) on intent errors. John Henry effects, expressed as an unwillingness to use automation, were hypothesized to increase as a function of operators' personal investment in unaided performance. **Background:** Misuse and disuse often occur because operators (a) cannot determine if automation or a nonautomated alternative maximizes the likelihood of task success (appraisal errors) or (b) know the utilities of the options but disregard this information when deciding to use or not to use automation (intent errors). Although appraisal errors have been extensively studied, there is a paucity of information regarding the causes and prevention of intent errors. **Methods:** Operators were told how many errors they and an automated device made on a target detection task. Self-reliant operators (high personal investment) could depend on their performance or automation to identify a target. Other-reliant operators (low personal investment) could rely on another person or automation. **Results:** As predicted, self-reliance increased disuse and decreased misuse. **Conclusion:** When the disuse and misuse data are viewed together, they strongly support the supposition that personal investment in unaided performance affects the likelihood of John Henry effects and intent errors. **Application:** These results demonstrate the need for a model of operator decision making that takes into account intent as well as appraisal errors. Potential applications include developing interventions to counter the deleterious effects of human–machine competition and intent errors on automation usage decisions.

INTRODUCTION

In the home, the workplace, and on the battlefield, people often have the option of performing a task manually or relying on automation. These automation usage decisions (AUDs) are of great interest to system designers and operator trainers because they influence the likelihood of task success. Inefficient AUDs often lower worker productivity and sometimes result in injury or death (e.g., Beck, Dzindolet & Pierce, 2002).

Viewing automation usage from a decision-making perspective allows specification of two types of suboptimal choices. Disuse is the underutilization of technology, employing manual control or a low level of automation (LOA) when the task could be better performed with a higher LOA. Misuse is overreliance, or use of a high LOA when the task could be better accomplished manually or with a lower LOA (Parasuraman & Riley, 1997).

Beck et al. (2002) proposed that disuse and misuse frequently result from appraisal and intent errors. Appraisal errors are evaluation failures; they occur when the perceived utilities (Dzindolet, Pierce, Beck, & Dawe, 2002) of the automated and nonautomated options fail to correspond with the actual utilities of the options. Unlike appraisal errors, intent errors are not caused by the inability of operators to assess the relative utilities of different LOAs. Operators committing intent errors know whether the automated or nonautomated alternative is most likely to produce a favorable task outcome. Nevertheless, they disregard these utilities and use a level of control that lowers the probability of task success.

Why Distinguish Between Appraisal and Intent Errors

Although it is well accepted that misjudgments of the utilities may produce disuse and misuse (DeVries & Midden, 2008; Dixon & Wickens, 2006; Dzindolet, Pierce, Beck, Dawe, & Anderson, 2001; Kantowitz, Hanowski, & Kantowitz, 1997; Madhavan & Wiegmann, 2007a; Madhavan, Wiegmann, & Lacson, 2006; Parasuraman, Bahri, Deaton, Morrison, & Barnes, 1992; Parasuraman & Miller, 2004; Seppelt & Lee, 2007; Wiegmann, 2002), there is a paucity of information regarding the causes, incidence, and prevention of intent errors. This may be a particularly significant omission in the literature because many instances of disuse and misuse could result from appraisal or intent errors.

Reportedly, some soldiers in the first Gulf War turned off useful automated aids before going into battle (Dzindolet & Beck, 2006). These suboptimal AUDs could have been appraisal errors; soldiers may have underestimated the value of the aids. Or they could have been intent errors. Soldiers may have recognized the benefits of automation but employed manual control for other reasons.

From an applied standpoint, intent errors need to be distinguished from appraisal errors because they frequently require different remedies. Education regarding the alternatives often prevents appraisal errors. For instance, pilots learn to rely on instruments rather than vision when they have difficulty determining the horizon. Education regarding the utilities is less likely to decrease intent errors. Amelioration of intent errors requires mitigating the impact of objectives that are incompatible with good performance. For example, craftsmen may initially oppose automation they believe reduces them to "button pushers" but become supporters of new technologies after status concerns are minimized.

A recent study by Beck, Dzindolet, and Pierce (2007) demonstrated the need to control intent as well as appraisal errors. In one condition, operators received feedback that an automated device was more accurate than their unaided target detection. Manipulation checks revealed that feedback eliminated or substantially reduced appraisal errors. Nevertheless, when choosing between automated and nonautomated control, operators relied on their own skills on 55% of the trials.

In another condition, participants received scenario training plus feedback. Scenario training, a technique designed to reduce intent errors, encouraged operators to compare unaided performance to the performance of an automated device. When used with informational feedback, scenario training produced a statistically significant reduction in intent errors, decreasing the disuse rate from 55% to 29%.

A key question left unresolved by Beck et al.'s (2007) study is, What caused these intent errors? Why did the majority of operators given feedback without scenario training refuse to use an aid they knew would increase the number of correct identifications? What motivated these operators to knowingly lower their performance?

John Henry Effects, Personal Investment, and Automation Disuse and Misuse

Many investigators (Bowers, Jentsch, Salas, & Braun, 1998; Miller & Parasuraman, 2007; Nass & Moon, 2000; Park & Catrambone, 2007; Rajaonah, Tricot, & Anceaux, 2008) have proposed that operators establish "relationships" with their machines. Ideally, operators will form cooperative associations with their machine "partners" (Klein, Woods, Bradshaw, Hoffman, & Feltovich, 2004; Madhavan & Wiegmann, 2007b), much as they do with human teammates.

Unfortunately, the history of technology (Binfield, 2004; Garson, 1995; Sheridan, 2002) is characterized by antagonistic as well as cooperative relationships between workers and automation. One explanation for the intent errors in Beck et al.'s (2007) study is that participants were unwilling to rely on automation because they saw the machine as a competitor or threat. Responding to automation as a challenger, competitor, or adversary is called a John Henry effect after the legendary railroad man who died racing the steam drill (Nelson, 2006; Watson, 1990).

Informal observation suggests that human–machine competition is most likely to affect AUDs when workers highly value unaided performance. For instance, officers who have trained for years to maneuver soldiers on a battle space are likely to bristle at the suggestion that

efficiently. The purpose of this experiment was to test the hypothesis that operators' personal investment in unaided performance increases the likelihood of John Henry effects.

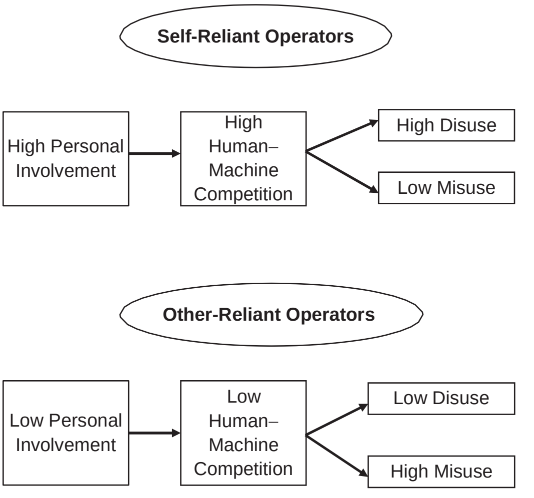

Figure 1. Hypothesized relationships of personal investment and human–machine competition on disuse and misuse.

Task, Design, and Hypotheses

On each of a series of detection trials, operators could rely on a human or machine to distinguish "friendly" from "enemy" helicopters. Unlike some studies (e.g., Dzindolet et al. 2001; Madhavan & Wiegmann, 2007a), the AUD was made before rather than after the target was shown. These kinds of decisions are commonplace. For example, a commander could send a manned or an unmanned aerial vehicle on a reconnaissance mission.

A 2 (operator: self-reliant, other-reliant) × 2 (machine reliability: inferior, superior) × 14 (trial blocks) mixed design was employed. Operator and trial blocks were within-subjects variables and machine reliability was a between-subjects variable. Self-reliant participants could depend on themselves or a combat identification device (CID) to identify the target. Those in the other-reliant condition could rely on a previous participant's performance or the CID's performance. Therefore, self-reliant but not other-reliant operators had the opportunity to become personally invested in unaided target detection. If the operator manipulation was effective, personal investment and human–machine competition should be greater in self- than in other-reliant conditions.

The optimality of the AUD depended on the relative accuracies of the CID and human. In the superior machine condition, the CID made more correct identifications over the long run. Relying on human control was a suboptimal AUD, an instance of disuse. If personal investment enhances the operator's preference for the nonautomated option, disuse should be greater among self- than among other-reliant operators.

In the inferior machine condition, the human was more accurate than automation. Relying on the relatively inaccurate CID constituted automation misuse. Because they are more personally invested in unaided performance, self-reliant operators are predicted to exhibit stronger preference for human control (less misuse) than other-reliant operators (Figure 1 illustrates the hypotheses).

The main effect for the trials variable is also predicted to be statistically significant. Some appraisal errors are expected on early trials before operators have sufficient opportunity to compare human with machine accuracy. Across trials, cumulative feedback should decrease appraisal errors, producing a statistically significant reduction in suboptimal AUDs.

The LOA that the operator relies on is one of many variables that influence the likelihood of a correct identification. Therefore, an inverse but imperfect correlation is expected between suboptimal AUDs and performance. Experimental manipulations that increase suboptimal AUDs are predicted to produce lower levels of performance.

METHOD

Participants

Serving as participants were 88 undergraduates (44 females and 44 males) enrolled at a comprehensive southeastern university served as participants. Random assignment was employed with the stipulations that each cell contained the same number of participants and an equal number of each gender. Procedures were approved by an institutional review board and were in accord with the guidelines for ethical conduct (American Psychological Association, 2001).

Instrumentation

The workstation was an Intel Pentium III, 864-MHz central processing unit equipped with 256 MB of random-access memory, a mouse, and keyboard. Slides were shown on a 38.1-cm V755 OptiQuest View Sonic Monitor driven by a Dell Dimension XPS B866 video card. Resolution was high color (16-bit), 1,024 × 768 pixels. A Visual Basic program presented the slides and recorded responses.

The targets were black-and-white photographs of 72 Black Hawk (friendly) and 72 Hind (enemy) helicopters. Some pictures were of complete helicopters, and others showed part of a helicopter. Of the slides, 136 were presented twice and 8 pictures once, yielding a total of 280 trials.

Procedure

Self-reliant operators. Participants were instructed that the task involved distinguishing friendly from enemy helicopters. On each trial, operators could rely on themselves or the CID to identify the target. Photographs of the two types of helicopters were placed on the workstation to assist the operators during the detection trials.

The participants' goal was to earn as many credit points as possible. Operators gained one credit point if they based credit on their performance and their targeting decision was correct or if they based credit on the machine's answer and it was right. They earned zero credit points if they based credit on themselves and their targeting decision was wrong or if they relied on the CID and it was incorrect. Operators received $5 at the end of the session if their total credit points exceeded the 50th percentile.

Each trial began with a "Credit Choice" screen on which participants elected to base the upcoming trial on nonautomated or automated control (Figure 2). Choices were indicated by clicking a button labeled "Credit Point For The Next Trial Will Be Based On My Response" or "Credit Point For The Next Trial Will Be Based On The Combat Identification Device's Response." This AUD yielded the main dependent measure.

Next, a target photograph was displayed for 0.75 s. Then, the "Operator Response" screen appeared. Participants clicked the "Fire" button or "Hold Fire" button, depending on whether they believed the photo was a friend or enemy. Operators attempted to identify the target, regardless of their decision on the Credit Choice screen.

The "Combat Identification Device Response" screen then emerged and indicated if the CID would fire or hold fire. Each trial concluded with the "Results" screen. It revealed (a) the operator's choice on the Credit Choice screen, (b) the operator's and CIDs' targeting decisions, (c) whether a friend or enemy was in the slide, and (d) if the operator received a credit point for that trial.

Counters located at the center of the Credit Choice screen provided running totals of errors made by the participant on the Operator Response screen and errors made by the machine on the CID Response screen. After operators learned whether the human was more or less accurate than the CID, any suboptimal AUDs were expected to result from intent rather than appraisal errors.

Unbeknownst to the operators, the CID's accuracy depended on their performance and the level of the machine reliability. For example, if an operator paired with the superior machine made 40 errors during the session, the CID made approximately 20 mistakes. If a participant working with the inferior machine made 15 errors, the CID made roughly 30 mistakes.

After four sample trials, operators were questioned to ensure that they understood the directions. The experimenter then left the room and the detection trials began.

Other-reliant operators. Like self-reliant operators, the goal of other-reliant operators was to earn as many credit points as possible. Participants assigned to the other-reliant conditions were treated identically to those in the

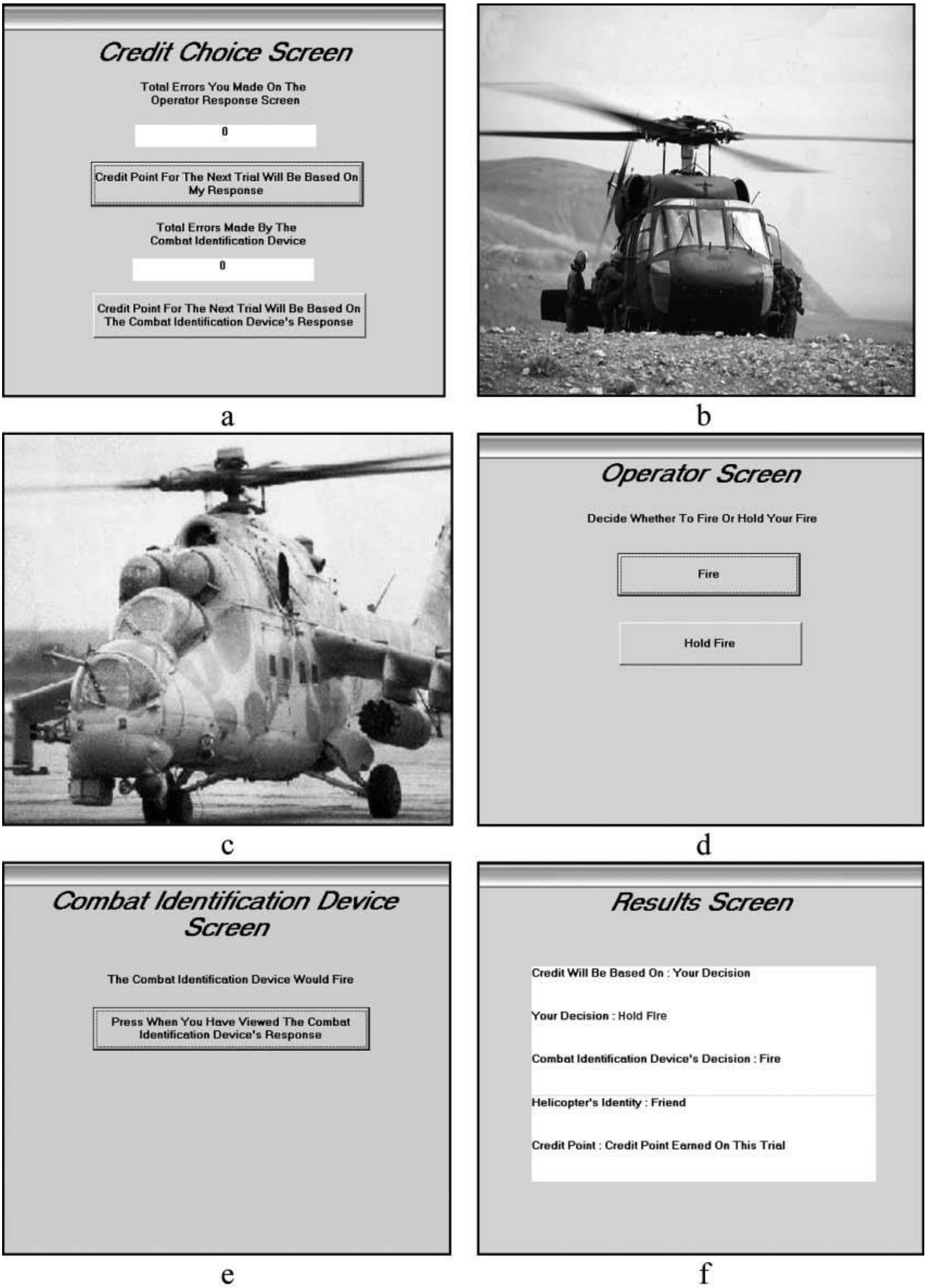

Figure 2. Sequence of screens composing a detection trial: Credit Choice screen (a), photograph of a friendly (b) or enemy helicopter (c), Operator Response screen (d), Combat Identification Device Response screen (e), and Results screen (f).

self-reliant conditions with these exceptions. On the Credit Choice screen, other-reliant students clicked a button labeled “Credit Point For The Next Trial Will Be Based On A Previous Operator’s Response,” or they pressed a button labeled “Credit Point For The Next Trial Will Be Based On The Combat Identification Device’s Response.”

The target slide was then shown, followed by the Operator Response screen. Other-reliant participants, however, did not attempt to distinguish friendly from enemy helicopters. Instead, they viewed a self-reliant operator’s choice to fire or hold fire. Each trial concluded with the CID Response and Results screens. Total mistakes made by a prior participant on the Operator Response screen and by the machine on the CID Response screen were displayed by error counters on the Credit Choice screen.

Operators assigned to the other-reliant groups were yoked to an individual in the self-reliant groups with respect to the gender of the participant and the machine reliability variable. For instance, assume a woman in the self-reliant condition worked with the superior machine, clicked “Fire” on Trial 32, and saw that the CID held fire. Then, a woman in the other reliant condition who worked with the superior machine saw that the previous participant fired on Trial 32 and that the CID held fire.

Manipulation checks. Participants responded to two five-item Likert-type items following the 280th trial. The first question, “Which was more important to you: earning credit points or answering (seeing a previous participant answered) correctly on the Operator Response screen?” assessed the operator variable. If self-reliance enhanced personal investment in unaided performance and human–machine competition, correct answers on the Operator Response screen should be more important to self than to other reliant participants.

The second item, “Do you think that you (the previous participant) or the combat identification device was more accurate in distinguishing friendly from enemy helicopters?” tested the machine reliability variable. If the manipulation was successful, operators in the superior conditions should rate the CID as more accurate than operators assigned to the inferior conditions. Furthermore, because yoking and immediate feedback were employed. There should be little difference in how self- and other- reliant operators rated the relative accuracy of the CID.

The investigator returned to the room following the manipulation checks. Operators received $5 if they obtained more than 210 credit points; otherwise, no money was given. Participants were thanked and debriefed.

RESULTS

The dependent variables were the frequency of suboptimal AUDs and the frequency of trials in which the operator received no credit point (NCP). The error variances associated with the superior machine condition were much greater than the error variances associated with the inferior machine condition. With suboptimal AUDs as the dependent measure, $F_{max}(2, 21) = 3.83$, $p < .01$, with NCPs as the dependent variable, $F_{max}(2, 21) = 3.21$, $p < .05$. Therefore, the levels of machine reliability were examined separately.

Two 2 (operator: self reliant, other reliant) × 14 (trial blocks) repeated measures ANOVAs were performed on the data of participants assigned to the superior machine condition, one for each dependent measure. Two similar ANOVAs were conducted on the responses of operators paired with an inferior machine.

Superior Machine Conditions

The main effect for the operator variable was statistically significant with suboptimal AUDs as the dependent variable, $F(1, 21) = 38.54$, $p < .001$, partial eta squared = .65. If the machine’s accuracy was superior to the human, self-reliant operators made more suboptimal decisions (M = 177.32) than other-reliant (M = 64.82) operators (Figure 3). A statistically significant main effect for the trial blocks variable was also obtained, $F(13, 273) = 3.02$, $p < .001$, partial eta squared = .13. Fewer suboptimal AUDs occurred on the later trial blocks. The Operator × Trial Blocks interaction was not statistically significant, $F(13, 273) = 1.58$, *ns*, partial eta squared = .07.

A significant main effect for the operator variable was also found if NCP was the dependent measure, $F(1, 21) = 15.44$, $p < .001$, partial eta squared = .42. Self-reliant operators

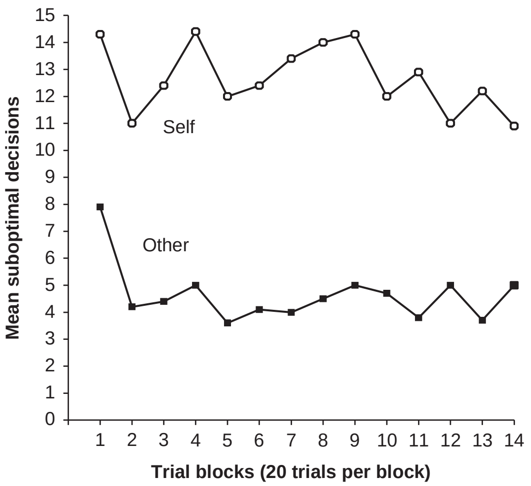

Figure 3. Mean suboptimal automation usage deci sions as a function of the operator variable and trial blocks for participants working with the superior machine.

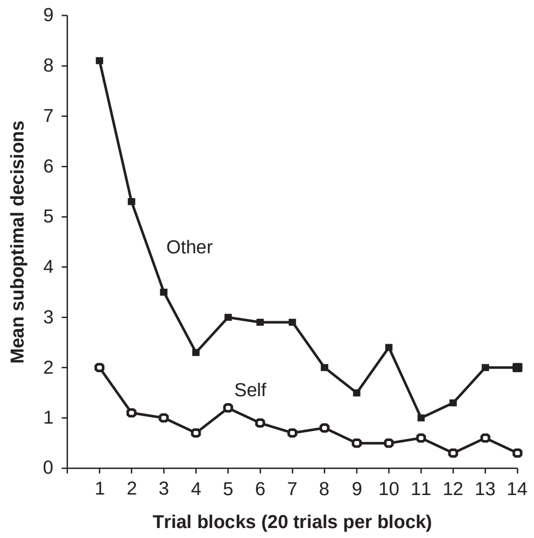

Figure 4. Mean suboptimal automation usage deci sions as a function of the operator variable and trial blocks for participants working with the inferior machine.

(M = 54.18) had more NCPs than other-reliant operators (M = 43.86). Trial blocks was also statistically significant, $F(1, 21) = 5.80$, $p < .001$, partial eta squared = .22. NCPs declined across trials. The two-way interaction was not statistically significant, $F(13, 273) = 1.58$, *ns*, partial eta squared = .07.

Inferior Machine Conditions

ANOVA yielded a statistically significant main effect for the operator variable with sub-optimal choices as the dependent variable, $F(1, 21) = 9.62$, $p < .01$, partial eta squared = .31. In the inferior machine condition, self-reliant operators committed more suboptimal AUDs (M = 40.09) than other-reliant (M = 11.36) operators (Figure 4). The trial blocks variable also attained statistical significance, $F(13,273)=16.45$, $p < .001$, partial eta squared = .44. Suboptimal AUDs were more frequent on early trial blocks. A statistically significant ordinal interaction was also found, F (13, 273) = 8.51, $p < .001$, partial eta squared = .29. Other-reliant operators exhib ited a greater decline in suboptimal AUDs across trials than self-reliant operators.

Analysis of the NCPs of participants paired with an inferior machine yielded a statistically significant main effect for the operator variable, $F(1, 21) = 5.80$, $p < .05$, partial eta squared = .22. Self-reliance operators made fewer NCPs (M = 68.50) than other-reliant operators (M = 73.91). Trial blocks was also statistically signifi cant, $F(1, 21) = 12.53$, $p < .001$, partial eta squared = .37. NCPs decreased across trials. The two-way interaction attained statistical significance, $F(13, 273) = 2.00$, $p < .05$, partial eta squared = .09.

Manipulation Checks

Correct responses on the Operator Response screen were more important to self-reliant (M = 3.41, SD = 1.11) than to other-reliant operators (M = 2.27, SD = 1.15), $t(43) = 5.18$, $p < .001$, suggesting that personal investment and human–machine competition were successfully manipulated. Responses to the second item, comparing the relative accuracies of the human and CID, found that machine reliability was successfully varied, $t(86) = 20.52$, $p < .001$. The superior machine received higher ratings (M = 4.27, SD = .82) than the inferior machine (M = 1.34, SD = .48). The mean accuracy rat ings of self-reliant operators (M = 2.86, SD = 1.52) and other-reliant operators (M = 2.75, SD = 1.73) were not significantly different, $t(43) = 0.76$, *ns*. Thus, no evidence was found indicating that self-reliant operators were more likely to underestimate their errors than other-reliant operators.

DISCUSSION

Personal Investment and John Henry Effects

As predicted, high personal investment in unaided performance increased disuse. Self-reliant operators committed more suboptimal AUDs and NCPs than other-reliant operators if the CID was more accurate than the human. Although manipulation checks indicate that they recognized the CID's superior accuracy, self-reliant operators' AUDs proved resistant to cumulative feedback. Their rate of suboptimal decisions never dropped below 54% on any trial block (Figure 3).

Other-reliant operators, having little or no personal investment in human control, were more responsive to cumulative feedback. They exhibited a distinct preference for the CID by the second trial block. Their rate of suboptimal AUDs across the last 260 trials was 22%.

Results were also consistent with the supposition that high personal investment decreases misuse. In the inferior machine condition, self-reliant operators made fewer suboptimal AUDs and had fewer NCP trials than other-reliant operators (Figure 4). Even on the first trial block, self-reliant operators seldom relied on the CID. Feedback indicating that they were more accurate than the machine did not further reduce suboptimal AUDs, perhaps due to a floor effect.

In contrast, other-reliant operators did not exhibit a strong initial preference for human control. Forty-one percent of their AUDs were suboptimal on the first trial block. Suboptimal AUDs gradually decreased as other-reliant operators learned that the CID was less accurate than the prior participant. When the disuse and misuse data are viewed together, they provide strong support for the prediction that personal investment in unaided performance increases the likelihood of John Henry effects.

As hypothesized, experimental conditions that increased suboptimal AUDs resulted in lower performance. Effect sizes, however, reveal that the operator and trial block variables had a greater impact on AUDs than on NCPs. NCPs were probably less affected by the experimental manipulations because performance is influenced by many variables in addition to personal investment and AUDs.

An alternative interpretation of these findings is that self-reliant operators underestimated their errors. No doubt, people are often less aware of their own errors than they are of mistakes made by others or by machines. In this study, however, immediate feedback on the Results screen was intended to minimize this tendency. This procedure appears to have been effective, as the manipulation check comparing human with CID accuracy found little difference in the ratings of self- and other-reliant participants.

Refusing to rely on automation of proven utility is one of many ways people express John Henry effects. John Henry effects could lead workers to destroy equipment, overemphasize machine failures, exaggerate their own skills, experience debilitating anxiety, become depressed, or organize to prevent mechanization. Predicting how John Henry effects will be manifested is a complex but important topic for future investigations.

The results of this and other studies emphasize the need to develop interventions to counter deleterious John Henry effects. Techniques, such as scenario training (Beck et al., 2007), which prompt operators to compare the utilities of automated and non-automated control are one means of decreasing suboptimal AUDs. The work of Miller (2002, 2004) on human–computer "etiquette" implies that John Henry effects will be reduced if operators regard automation as a partner rather than a competitor. Etiquette may affect trust, which in turn influences the probability of intent errors (Dzindolet, Beck, & Pierce, in press; Lee & Moray, 1992; Lee & See, 2004; Lees & Lee, 2007; Merritt & Ilgen, 2008; Parasuraman & Miller, 2004).

Intent Errors, Misuse, and Disuse

In this investigation, some appraisal errors undoubtedly occurred on the early trials. Still, the preponderance of evidence indicates that most suboptimal AUDs were errors of intent. Manipulation checks found that almost every participant recognized whether the human or CID was more accurate. Also, yoking was employed. With respect to judging the utilities, self- and other-reliant operators faced cognitively identical tasks. The substantial differences in the disuse and misuse rates of self and other-reliant operators can be attributed only to intent errors.

It is very important for researchers to deter mine if intent errors affect the AUDs of highly trained as well as novice operators. Although this issue needs to be tested in an automated setting, investigations contrasting actuarial and clinical judgments (Dawes, 1994; Dawes, Faust, & Meehl, 1989; Grove, Zald, Lebow, Snitz, & Nelson, 2000) often find that professionals are not immune to errors of intent. Almost every graduate student in the behavioral sciences is exposed to the research demonstrating that actu arial judgments are frequently more accurate than clinical judgments. Nonetheless, personnel directors, therapists, and other professionals often rely more on their subjective impres sions than on objective data when making life-changing assessments.

If suboptimal AUDs were solely attributable to appraisal errors, disuse and misuse could be largely eliminated by correcting misjudgments of the utilities of the automated and non-automated alternatives. The potential for intent errors necessitates a more complex and com- prehensive model of operator decision making. AUDs must be viewed as governed by multiple objectives, some of which may be incompatible with achieving task success.

This experiment demonstrated that operators' personal investment in non-automated performance affects the likelihood of John Henry effects and intent errors. The challenge for investigators is to identify other variables that determine the impact of intent errors on disuse and misuse. After these conditions have been ascertained, interventions must be designed to control intent errors as well as appraisal errors.

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