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The Effects of Age and Working Memory Demands on Automation-Induced Complacency

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THE EFFECTS OF AGE AND WORKING MEMORY DEMANDS ON AUTOMATION-INDUCED COMPLACENCY

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ABSTRACT

Complacency refers to a type of automation use expressed as insufficient monitoring and verification of automated functions. Previous studies have attempted to identify the age-related factors that influence complacency during interaction with automation. However, little is known about the role of age-related differences in working memory capacity and its connection to complacent behaviors. The current study examined whether working memory demand of an automated task and age-related differences in cognitive ability influence complacency. Working memory demand was manipulated in the task with two degrees of automation (i.e., information and decision). A younger and older age group was included to observe the effects of differences in working memory capacity on performance in a targeting task using an automated aid. The results of the study show that younger and older adults did not significantly differ in complacent behavior for information or decision automation. Also, individual differences in working memory capacity did not predict complacency in the automated task. However, these findings do not disprove the role of working memory in automation-induced complacency. Both age groups were more complacent with automation that had less working memory demand. Our findings suggest systems that utilize both higher and lower degrees of automation could limit overdependence. These results provide implications for the design of automated interfaces.

ACKNOWLEDGMENTS

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INTRODUCTION

People depend on a wide variety of automated technologies to support accurate and effective decision-making; for example, these technologies are used in domains such as aviation, healthcare, and transportation. When automation is highly reliable, users will tend to increasingly depend on the system. This high level of dependence, or automation-induced complacency, can lead the user to make incorrect assumptions that automation is more reliable than it is (Billings, Lauber, Funkhouser, Lyman, & Huff, 1976). One consequence is that users are less likely to notice when the automation does fail. Thus, complacency is a state of dependence where a user fails to notice imperfect automation. When the user poorly monitors the system and does not detect a fault, performance consequences can result (Parasuraman & Manzey, 2010). Users may have a delayed reaction to the presence of an automation failure or might miss the failure altogether.

There are a limited number of known system and human-related factors that are connected to complacency (Parasuraman & Manzey, 2010). Complacency effects are most likely to emerge when the automated system is designed in a particular way. System-related factors include automation reliability and task complexity (Parasuraman, Molloy, & Singh, 1993; Parasuraman & Riley, 1997). Individuals have difficulty detecting automation failures when the system is highly reliable and the task is more demanding (Bailey & Scerbo, 2007). In addition to system-related factors, there are individual differences that can induce greater dependence on the automation. The human-related factors that are known to impact complacent behavior include system experience (Molloy & Parasuraman, 1996), trust in automation (Muir & Moray, 1996), and complacency potential (Singh, Molloy, & Parasuraman, 1993b). Positive attitudes and experiences from automation use limit an individual's ability to detect automation failures (Bailey & Scerbo, 2007). Aside from individual differences, there has been a lack of research examining group differences in automation-induced complacency.

One main source of group differences in automation complacency is age, such that older adults are more complacent with automation than younger adults (Ho, Wheatley, & Scialfa, 2005). Ho, Wheatley, and Scialfa (2005) examined the effects of age on complacency using a decision aid in a medication management task. The researchers found that older adults depended on imperfect automation more than younger adults, yet were unable to determine the reason for this age disparity. Older adults might be more prone to complacent behavior because they have greater trust in automation and experience greater mental workload compared to younger adults (Ho, Wheatley, & Scialfa, 2005). However, most research on age differences in automation use requires multi-tasking to operate complex automation. Since older adults have age-related decrements in cognition, they have fewer resources to perform complex mental tasks (Verhaeghen & Cerella, 2002). Therefore, the high cognitive demands necessary to detect system failures over a long duration may influence older adults to over-depend on automation.

A potential explanation suggested for the divide between age groups' complacency behavior has been age-related reductions in working memory (Ho, Kiff, Plocher, & Haigh, 2005). Working memory is a cognitive system that provides temporary storage and manipulation of information that is used in many complex tasks (Baddeley, 1992). Due to age-related changes in cognition, working memory capacity significantly declines after the age of 60 (Morris, Gick, & Craik, 1988). Since complacent behavior requires fewer cognitive resources, older adults might be more susceptible to depend on automation when it has greater working memory demand.

Researchers have recently explored the role of working memory on automation use and found that individual differences in working memory capacity predicted performance in an automated UAV task (de Visser, Shaw, Mohamed-Ameen & Parasuraman, 2010). Individuals with greater working memory capacity had higher performance. High working memory capacity has also been shown to minimize the negative effects associated with increasingly supportive, but faulty automation (Rovira, Pak, & McLaughlin, accepted with revisions). Even though these studies were limited to younger adults, the results indicate that age decrements in working memory capacity should decrease older adults' performance in automated tasks.

There are two main aspects of working memory that contribute to older adults' complacent behavior with automated technologies (Ho, Kiff, Plocher, & Haigh, 2005). The first is that older adults form inaccurate decision making when using automation and struggle to determine the correct choice. When older adults have an insufficient understanding of the automated aid, they might believe the aid is reliable and not verify its recommendation. If older adults are not able to adequately compare their own decision to the automation's advice, they should fail to notice the presence of system failures. The second is that due to their reduced working memory capacity, older adults are unable to judge the accuracy of automation (Ho, Kiff, Plocher, & Haigh, 2005; Olson, Fisk, &

Rogers, 2009). Working memory is needed to activate and maintain useful information (e.g., relevant task goals) for later use. Diminished working memory may prevent users from keeping track of previous automation failures. When older adults need to retain several task goals at once, their working memory becomes limited by distractions from multitasking (Park, Smith, Dudley, & Lafronza, 1989). If older adults' reduced working memory makes it harder to detect or remember automation failures, they will have a distorted view of the system.

We assume older adults' relative complacency with automation is due to a mismatch between the working memory demands of the task and working memory capacity of the person (Ho, Kiff, Plocher, & Haigh, 2005). If working memory capacity plays such a central role in automation complacency, we should observe the opposite relationship as well: reduced complacency in older adults when the automation has been designed to demand relatively fewer working memory resources. The design of Ho, Wheatley, & Scialfa's (2005) study precludes this determination because the working memory demand of the tasks was not manipulated to vary during the experiment. Thus, it is unclear whether the high working memory demand of those tasks contributed to the difference in complacency between younger and older adults.

Current Study

The goal of the experiment was to examine the role of age-related differences in working memory on automation-induced complacency. If complacency is related to working memory, then altering the working memory demands of the task should affect complacency. Fortunately, the working memory demands of automation are related to the quantity of information presented to the user through the amount of support provided by automation (i.e., degrees of automation (DOA)) (Parasuraman, Sheridan, & Wickens, 2000; Sheridan & Verplank, 1978). Therefore, we can change the working memory demands of the task by altering the DOA presented to the user.

Higher DOAs are associated with greater performance in addition to diminished cognitive demand (Wickens, Li, Santamaria, Sebok, & Sarter, 2010). Since the automation is taking on more of the task for the user, cognitive demand is reduced under a higher DOA. This leaves the user with more cognitive resources at higher DOAs. Thus, working memory demands should lessen and detection of automation failures (i.e., verification behaviors) should increase as older adults move from a lower DOA towards a higher DOA.

We expected to find greater age-related differences in complacency as working memory demands increased. Ho, Wheatley, and Scialfa (2005) only used a high DOA (with concomitantly high working memory demands) to examine differences in complacency between younger and older adults. Therefore, we used two DOAs that should vary in working memory demand in order to investigate the effects of lower (i.e., information automation) and higher (i.e., decision automation) DOAs on complacency.

We tested that information automation had greater working memory demand than decision automation by examining the relationship between working memory capacity and task accuracy. We expected that younger adults would experience less working memory demand than older adults and their higher working memory capacity would be less predictive of task accuracy. Since older adults should have lower working memory capacity, and lower DOAs have shown greater working memory demand, we hypothesized that working memory capacity of older adults would be more predictive of task accuracy for information automation than decision automation.

This study utilized a low-fidelity targeting simulation to analyze the accuracy and speed of user selections. Since higher DOAs have been linked with reduced cognitive demand (Onnasch, Wickens, Li, & Manzey, 2014), we hypothesized that participants would perform better under decision automation than information automation. Older adults were predicted to have lower working memory capacity than younger adults because of changes in fluid intelligence. Based on these age-related changes in cognitive abilities, we predicted a main effect of age group on task accuracy and completion time, where younger adults would outperform older adults.

We can infer the extent to which participants are complacent by analyzing their pattern of performance when the automation succeeds (i.e., reliable automation) and fails (i.e., unreliable automation). Low task accuracy for unreliable automation and high task accuracy for reliable automation indicates higher complacency because the user is relying heavily on the system without monitoring for failures. Therefore, we examined task accuracy for reliable and unreliable automation trials across two DOAs and age groups. We hypothesized that information automation would result in a greater difference in complacency between the age groups than at decision automation. We anticipated this result because the high working memory demand of information automation should limit only older adults' performance. Thus, lower working memory capacity should affect older adults' ability to verify information provided by the automated system.

METHODS

Participants

Forty-six undergraduate students were recruited through the Clemson University Sona Systems Participant Pool website and were given course credit for their participation. We recruited 44 older adults (ages 65-75) from the local area and compensated them $25 for their time. Both age groups were tested separately; however, up to 6 participants of the same age group were tested at one time. All participants worked independently at individual workstations.

Tasks

Targeting Task

The tasks for this study were adapted from prior research that used an automated system in the context of a low-fidelity unmanned aerial vehicle (UAV) simulation (Rovira, McGarry, & Parasuraman, 2007). The primary task for this study was to quickly find the closest combination of friendly (green) and enemy (red) units in terms of distance apart on the grid (Figure 1). The headquarters (orange) unit was used to determine the best answer when more than one friendly and enemy unit pairing had the shortest distance. Battalion (yellow) units were included in the grid as distractor targets. The grid always displayed 3 friendly units, 3 enemy units, 3 battalion units, and 1 headquarters unit. Automation was presented in the form of a table, which showed distances and unit combinations needed by participants to complete the primary task.

Communications Task

The secondary task consisted of checking for a specific call sign and clicking a corresponding button when it appeared on screen (Figure 1). The call sign was comprised of a single word and number combination (e.g., Hunter-6). The program randomly switched to a different call sign (14 total) every 5 seconds as the participant completed the primary task.

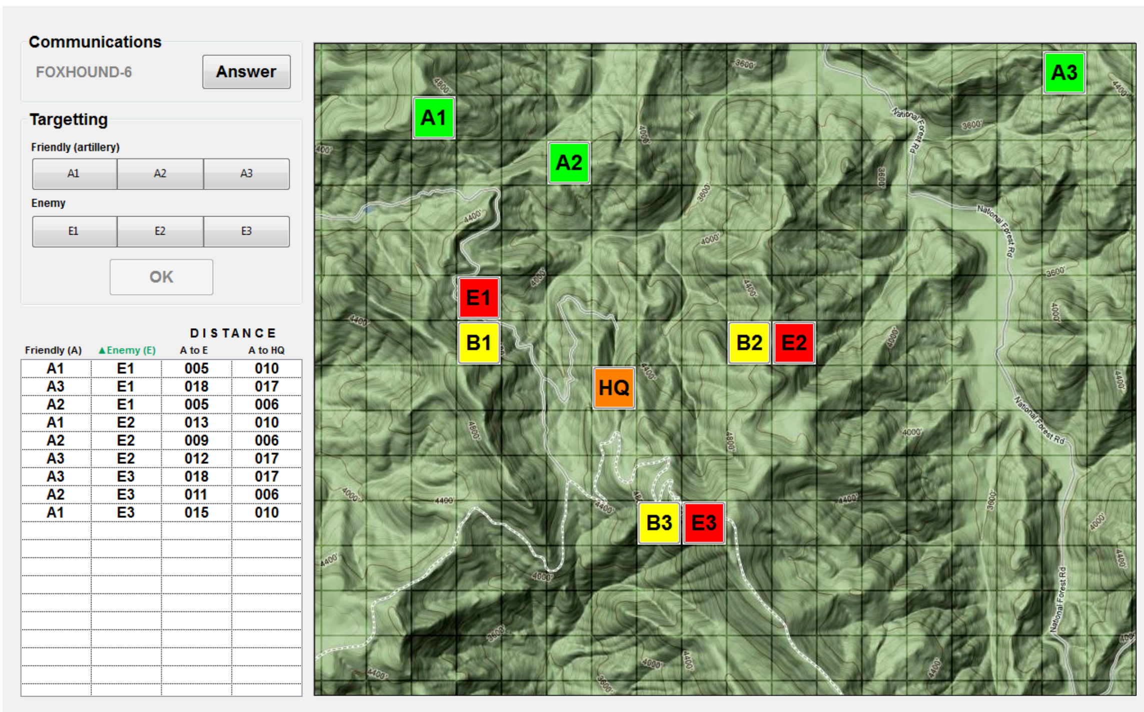


Figure 1. Screenshot of targeting and communications tasks. Features communications panel (top-left), targeting input panel (middle-left), automation table (bottom-left), and grid (right).

Design

The experiment was a 2 (age group: young, old) x 2 (DOA: information, decision) x 2 (trial reliability: unreliable, reliable) mixed-subjects design. Age group was a between-subjects independent variable. DOA and trial reliability were within-subjects independent variables.

Participants completed eight blocks of 160 total trials (20 trials per block), where each block displayed either information or decision automation (Appendix A). A randomized block design was utilized within each age group. Thus, participants were first presented with either four information automation blocks or four decision automation blocks before continuing to the other DOA. The assignment of presentation order was randomized for every participant prior to recruitment.

The working memory demand of the targeting task was manipulated by using two DOAs (i.e., information and decision) in the automation table. Information automation displayed all possible friendly and enemy unit combinations in the grid (9 total) and sorted the order of enemy units (e.g., E1-E3) (Appendix A). This DOA placed greater demand on working memory to locate the best answer because of the increased amount of information shown and the lack of useful organization within the automation table. Decision automation presented the top three friendly and enemy unit combinations (Appendix A). This DOA sorted the information based on importance, so that the shortest distance for a unit combination was shown at the top. Decision automation placed less demand on working memory to locate the best answer because of the reduced amount of information presented and the improved organization within the automation table.

The overall automation reliability was set at 80% because operators will depend upon imperfect automation above an approximate level of performance (70%) (Wickens & Dixon, 2007). In each block of 20 trials, 16 trials were reliable and the remaining 4 trials were unreliable. An unreliable trial contained inaccurate distance values between friendly and enemy units within the automation table (Appendix A). The first automation failure did not occur until the 10^{th} trial, so that users could rebuild trust after each block. Subsequent automation failures were distributed randomly throughout the remaining trials.

The dependent variables were targeting accuracy, targeting time, complacency potential, and working memory capacity. *Targeting accuracy* was measured by the mean rate of optimal responses for each automation block. An optimal response is the correct identification of the closest pair of friendly and enemy units in the targeting task. *Targeting time* was measured by the average duration (in seconds) it took participants to complete each trial. *Complacency potential* was comprised of subjective ratings on the Complacency Potential Rating Scale (CPRS). *Working memory capacity* measured the sum of perfectly recalled sets of letters on the Automated Operation Span (AOSPAN) task.

Materials

Equipment

The tasks were programmed in Xojo for Windows and presented (maximized with no visible user interface) on a 19-inch LCD monitor set at a resolution of 1024 x 1280. Participants sat approximately 18 inches away from the computer screen and interacted primarily with a mouse and a keyboard. Participants were told to adjust equipment as necessary. Six-foot tall cubicle dividers separated each computer station.

Surveys & Abilities

Demographic and health information were collected from each participant. The following cognitive abilities were assessed: perceptual speed (Digit-Symbol Substitution; Wechsler, 1997), vocabulary (Shipley Vocabulary; Shipley, 1986), and working memory (Automated Operation Span (AOSPAN); Unsworth, Heitz, Schrock, & Engle, 2005). Instructions for the AOSPAN can be found in Appendix B. These measures were chosen because they are reliable indicators of their respective abilities (e.g., Czaja et al., 2006).

In the AOSPAN, participants were instructed to complete simple math problems while remembering the order of individual letters that were presented after solving each problem. Younger adults needed to correctly answer at least 85% of the math problems and recall as many letters as possible. Consistent with other aging literature (Zeintl & Kliegel, 2007), older adults needed to correctly answer at least 80% of the math problems. The AOSPAN score consisted of the sum of all perfectly recalled letter sets, where higher scores indicated greater working memory capacity. AOSPAN scores under two standard deviations away from the mean were established as additional exclusion criteria because a score that low indicates that participants were not performing both tasks.

A blocked design for the UAV simulation allowed us to administer a history-based trust measure using a survey adapted from Lee and Moray (1992) (Appendix C) and the NASA-TLX (Hart & Staveland, 1988) at the end of each block of trials. Measures of dispositional trust (Merritt & Ilgen, 2008) using a survey developed by Jian, Bisantz, and Drury (2000) (Appendix D) and automation complacency potential using the

CPRS (Singh, Molloy, & Parasuraman, 1993a) (Appendix E) were used to assess age differences.

Procedure

Participants were seated at individual computers and provided with informed consent. After giving verbal consent, participants were instructed to complete the AOSPAN task. The participants then filled out the demographics form and finished the remaining cognitive ability measures (i.e., Digit Symbol Substitution and Shipley Vocabulary). The experimenter told participants to open and observe the instructions screen for the UAV simulation. Participants were told the following: "In this experiment, you will have two tasks. Please keep in mind that you will perform both tasks simultaneously. The first task will be to monitor the communications panel for the call sign Hunter-6. When you see Hunter-6, you should click the answer button. The second task will be to target enemy units with the closest friendly unit as quickly as you can. You will do this by first selecting a friendly unit from the list of buttons in the targeting input and then select an enemy target from the list of buttons and click OK. The computer aid will sometimes help you with this task by showing you the distances between friendly and enemy units. Sometimes, two sets of targets will have the same distance. In this case, you will pick the friendly unit with the shortest distance to the headquarters. Sometimes the computer aid will give you lots of information, other times it will give you much less information. The computer aid can be very reliable but it is not perfect all the time." After these instructions, the experimenter had participants attempt 8 practice trials (all reliable automation with no feedback). The first half of the practice trials featured information automation and the latter half featured decision automation. After the practice trials, the experimenter answered any questions before the participants started the actual task.

Participants then proceeded through each block of real trials. As participants completed the tasks, the units inside the grid (i.e., friendly, enemy, battalion, and headquarters) and the information within automation table (i.e., distance values and unit pairings) changed after each trial. During the experiment, a screen appeared to indicate when participants lingered too long on a particular trial. If participants did not input an answer within the set time limit, the program would automatically continue to the next trial. Younger adults had 10 seconds to complete each trial, while older adults had 20 seconds. Older adults had more time for the task because of normative age-related differences in psychomotor speed (Salthouse, 1985). Time limits were based on an analysis of "timed out" trials (i.e., the participant did not answer quickly enough) from pilot testing the task with each age group. Between each block of trials, participants filled out the NASA-TLX survey and a brief history-based trust measure. When participants completed the automation program, the computer presented them with the dispositional trust and CPRS surveys. At the conclusion of the experiment, the experimenter debriefed participants and provided them compensation for their time.

RESULTS

Eight participants that met the exclusion criteria on the AOSPAN measure were eliminated. From that total, 5 participants (3 younger and 2 older adults) were removed because they performed below a set value (i.e. less than 80% for older adults and 85% for younger adults) on the math portion of the task. Two younger adults were eliminated due to obtaining a low working memory capacity score (i.e., scores under 2 standard deviations away from the mean). Only 1 younger adult was removed because of data loss from a computer shutting down during testing. The remaining 40 younger adults (*M* = 18.30, *SD* = 0.79) and 42 older adults (*M* = 70.00, *SD* = 3.19) were used in the analysis of all dependent variables. Participant demographics can be found in Table 1.

Table 1
Participant Demographic Frequencies by Age Group

Category	Younger Adults	Older Adults
Gender		
Female	23	24
Male	17	18
Race/Ethnicity		
Asian	2	1
Black/African-American	2	0
White	33	41
Hispanic/Latino	2	0
Other	1	0
Health		
Fair	0	4
Good	7	10
Very Good	26	21
Excellent	7	7
Highest Education		
High school graduate/GED	33	0
Vocational training	0	1
Some college/Associate's degree	7	9
College graduate	0	11
Master's degree (or other post-grad)	0	18
Doctoral degree (PhD, MD, EdD, etc.)	0	3

Before starting the analyses, trials that “timed out” (i.e., the participant did not answer quickly enough) were removed. The remaining results are structured to discuss each hypothesis and the accompanying analyses. We examined age-related differences in the AOSPAN task, the amount of working memory demand for each automated aid, differences in complacency potential between age groups, performance (completion time and accuracy) in the targeting task, and the role of working memory capacity in complacency. For the following analyses, significance is defined as an alpha level of .05.

Cognitive Abilities

Working memory capacity was examined as part of a larger set of measures to check for age-related differences in cognitive abilities (see Table 2). Working memory capacity on the AOSPAN task was calculated by summing the length of each correctly recalled letter set (between 3 and 7 letters long). For example, if the individual correctly remembered three 5 letter strings, their total score would be 15. The possible scores ranged from 0 to 75. There was a significant effect for age, $t(80) = 4.61$, $p < .001$, $\eta_p^2 = .21$, with younger adults ($M = 38.05$, $SD = 13.99$) scoring higher for working memory capacity than older adults ($M = 23.29$, $SD = 14.94$).

Consistent with prior aging research (Wechsler, 1981; Shipley, 1986) older adults scored significantly higher than younger adults on the Shipley Vocabulary test and older adults scored significantly higher than younger adults on the Digit-Symbol Substitution task (both $p < .001$) (Table 2). Only the Digit-Symbol Substitution task violated of homogeneity of variance as assessed by Levene's Test for Equality of Variances. After we used the Welch-Satterthwaite method to make adjustments for this cognitive ability test, we still observed significant differences between age groups ($p < .001$). The differences on these cognitive ability measures confirm the expected age-related changes in cognition between the groups.

Table 2
Summary of Means and Standard Deviations for Scores on Cognitive Ability Measures

	Younger Adults		Older Adults	
Measure	*M*	*SD*	*M*	*SD*
Automated Operation Span[a]	38.05	13.99	23.29	14.94
Digit Symbol Substitution[b]	1090.81	113.25	1773.19	422.10
Shipley Vocabulary[c]	29.38	3.03	36.02	2.31

Note. [a]Total number of correctly recalled letter sets. Scores are out of a possible 75. [b]Time to identify an incorrect trial in milliseconds. [c]Total correct. Scores are out of a possible 40.

Working Memory Capacity and Targeting Accuracy

We examined the relationship between working memory capacity and targeting accuracy to confirm differences in working memory demand for information and decision automation. Targeting accuracy was the mean proportion of selecting correct pairs of friendly and enemy units. High accuracy can imply complacent behavior because individuals lacking in working memory capacity should have greater dependence on the automated aid when experiencing greater demand. Information automation was expected to demand more working memory because it provided less automated support in the task. Thus, we hypothesized that working memory capacity scores would predict participants' targeting accuracy more for information automation than decision automation. We also anticipated that older adults' lower working memory capacity scores would predict targeting accuracy more than younger adults' higher working memory capacity scores. Simple linear regressions were calculated to regress targeting accuracy on working memory capacity scores. In the following regression analyses, we separated by age group and DOA to assess both hypotheses.

For older adults using information automation, working memory capacity scores accounted for 18.2% of the variance in targeting accuracy (F (1, 41) = 8.88, p < .01, $R^2_{adjusted}$ = .16). Working memory capacity scores positively correlated with targeting accuracy (β = .004, t(41) = 2.98, p < .01) (Figure 2). For older adults using decision automation, working memory capacity scores accounted for 11.3% of the variance in targeting accuracy (F (1, 41) = 5.10, p < .05, $R^2_{adjusted}$ = .09). Working memory capacity scores again positively correlated with targeting accuracy (β = .004, t(41) = 2.26, p < .05) (Figure 3). The results confirmed that information automation had relatively higher working memory demand than decision automation for older adults.

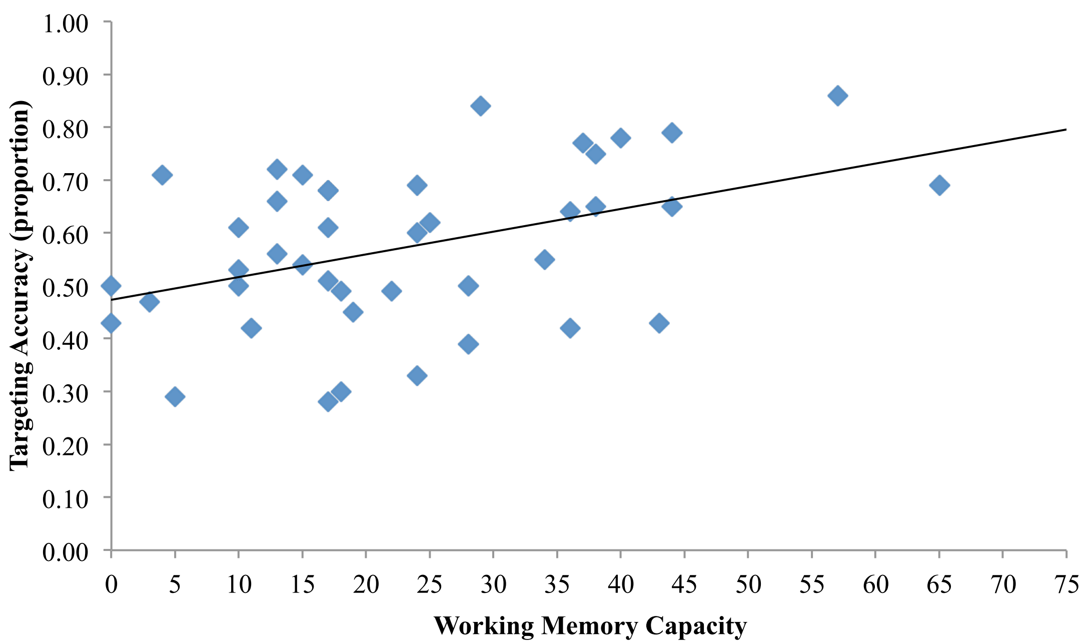


Figure 2. Older adult working memory capacity scores predicting targeting accuracy for information automation.

We regressed targeting accuracy on younger adults' working memory capacity scores similar to the older adult analyses discussed above. As expected, younger adults' high working memory capacity scores did not significantly predict targeting accuracy for information or decision automation. Thus, older adults experienced greater working memory demand in the targeting task than younger adults. Unlike older adults, younger adults experienced equivalent working memory demand for information and decision automation. The result indicates that younger adults were not as affected by the differences in working memory demand for information and decision automation because of their high working memory capacity.

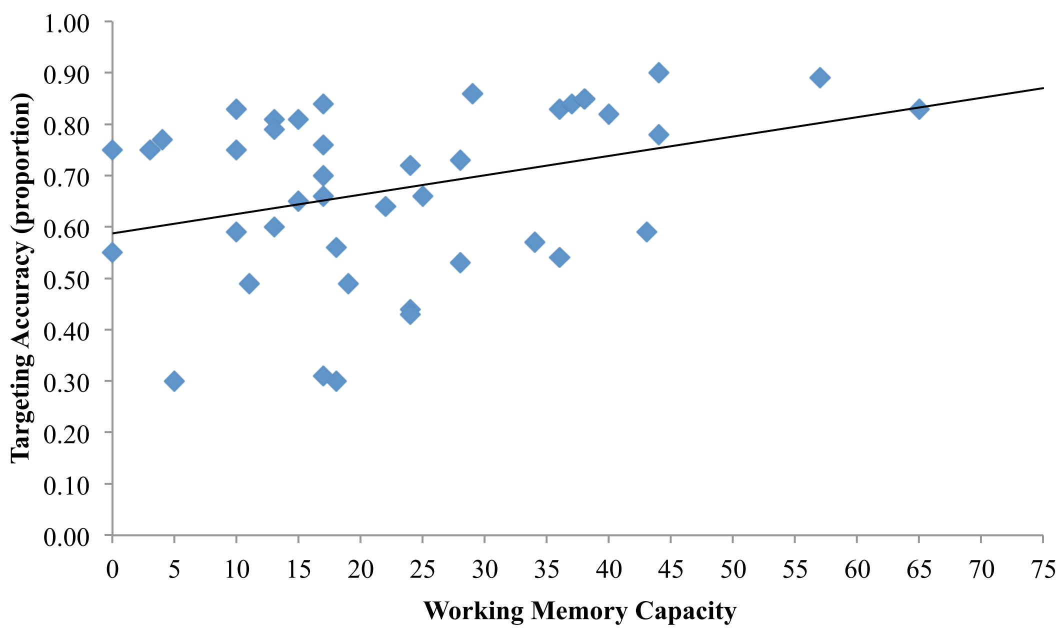


Figure 3. Older adult working memory capacity scores predicting targeting accuracy for decision automation.

Complacency Potential

We analyzed a measure of complacency potential to confirm that older adults exhibited greater complacency potential compared to younger adults. An independent samples *t*-test compared age groups on complacency potential. There was a violation of homogeneity of variance as assessed by Levene's Test for Equality of Variances. Thus, we made adjustments to the degrees of freedom using the Welch-Satterthwaite method. As expected, older adults (M = 46.83, SD = 3.66) had higher complacency potential than younger adults (M = 43.05, SD = 5.34), $t(68.55) = -3.72$, $p < .001$, $\eta_p^2 = .15$. The result indicates the influence of age on attitudes towards automation.

Targeting Task

Task Time

Next, we hypothesized a main effect of DOA with faster task times with decision automation (a higher DOA with more of the task automated) than information automation (a lower DOA). We expected a main effect of age group, such that younger adults would make faster selections than older adults. Average task time was the number of seconds it took participants to match a friendly and enemy unit. A 2 (age group: young, old) x 2 (DOA: information, decision) x 2 (trial reliability: reliable, unreliable) repeated measures ANOVA for targeting task time revealed significant main effects for DOA (F (1, 80) = 31.71, $p < .001$, $\eta_p^2 = .28$) and age (F (1, 80) = 227.67, $p < .001$, $\eta_p^2 = .74$) (see Table 3). There were no significant main effects for trial reliability or any significant 2 or 3-way interactions. Participants were faster with decision automation (M = 7.31, SD = 2.93) than information automation (M = 8.32, SD = 2.90). Younger adults were faster (M = 5.34, SD = .95) than older adults (M = 10.17, SD = 2.16). The results confirm the expected main effects for age group and DOA. The lack of an interaction between age, DOA, and trial reliability indicates that both age groups might have similar dependence on automation.

Table 3

Summary of Means and Standard Deviations for Task Time

	Younger Adults		Older Adults	
Trial Reliability and DOA	*M*	*SD*	*M*	*SD*
Unreliable Information Automation	5.69	0.86	10.67	2.06
Reliable Information Automation	5.79	0.77	10.78	1.93
Unreliable Decision Automation	4.92	1.00	9.65	2.50
Reliable Decision Automation	4.91	0.93	9.58	2.24

Task Accuracy

In addition to targeting task time, the next measure used to infer complacent behavior was targeting task accuracy. We expected a significant interaction between age, DOA, and trial reliability. Additionally, we hypothesized that participants would be more accurate with decision automation than information automation and younger adults would have greater accuracy than older adults. A 2 (age group: young, old) x 2 (DOA: information, decision) x 2 (trial reliability: reliable, unreliable) repeated measures ANOVA for targeting task accuracy revealed significant main effects for DOA (F (1, 80) = 44.95, $p < .001$, $\eta_p^2 = .36$) and trial reliability (F (1, 80) = 47.76, $p < .001$, $\eta_p^2 = .37$) (Table 4). Participants were more accurate with decision automation ($M = .69$, $SD = .16$) than information automation ($M = .58$, $SD = .15$). Participants were more accurate with reliable ($M = .69$, $SD = .19$) than unreliable automation ($M = .42$, $SD = .26$). The results confirm the expected main effects for trial reliability and DOA. There were no significant main effects for age or any significant 3-way interactions. However, there was one significant 2-way interaction between DOA and trial reliability, F (1, 80) = 8.82, $p < .01$, $\eta_p^2 = .10$ (see Figure 4).

Table 4

Summary of Means and Standard Deviations for Task Accuracy

	Younger Adults		Older Adults	
Trial Reliability and DOA	*M*	*SD*	*M*	*SD*
Unreliable Information Automation	0.40	0.26	0.39	0.27
Reliable Information Automation	0.63	0.18	0.62	0.20
Unreliable Decision Automation	0.44	0.32	0.44	0.31
Reliable Decision Automation	0.80	0.20	0.73	0.21

The source of the significant 2-way interaction between DOA and trial reliability was a greater difference in accuracy between DOA for reliable automation, F (1, 80) = 83.63, $p < .001$, $\eta_p^2 = .51$, than for unreliable automation, F (1, 80) = 3.46, $p = .07$, $\eta_p^2 = .04$ (Figure 2). We also examined accuracy for reliability simple main effects, that is, the differences between reliable and unreliable trials for each DOA separately. There was a significant difference in accuracy between reliable and unreliable trials for information automation, F (1, 80) = 34.66, $p < .001$, $\eta_p^2 = .30$, and for decision automation, F (1, 80) = 48.47, $p < .001$, $\eta_p^2 = .38$.

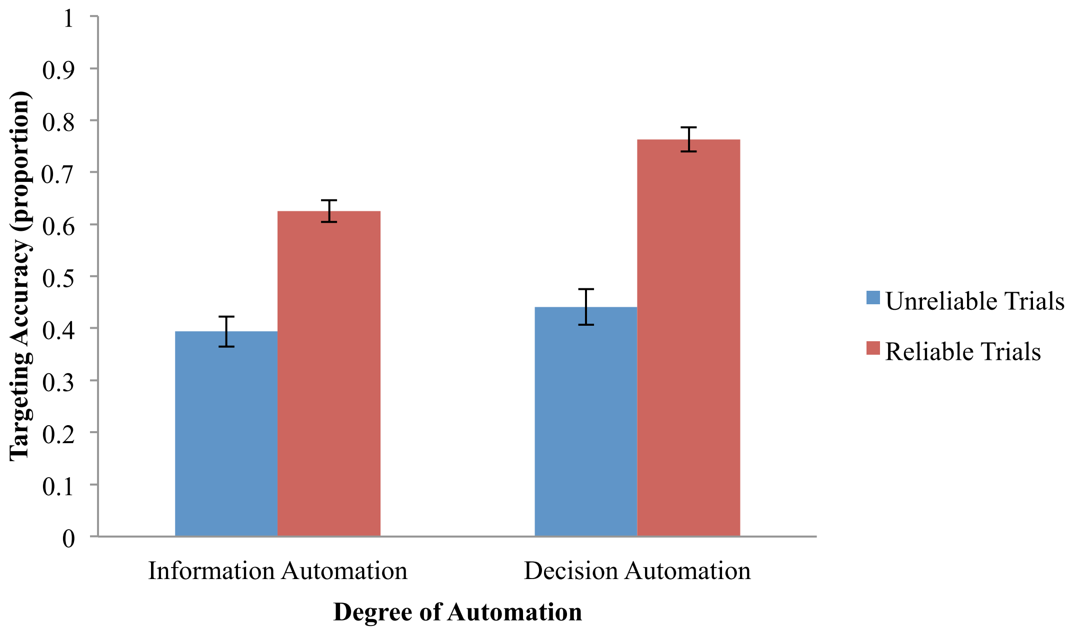


Figure 4. Targeting accuracy shown by trial reliability type for information and decision automation. Error bars represent standard error of the mean.

Working Memory Capacity and Complacency

A hierarchical linear regression was conducted to predict objective and subjective measures of complacency based on working memory capacity scores and age. In the hierarchical regression, predictors were entered in steps. Hierarchical regressions allowed us to examine unique variance by statistically controlling for the influence of variables entered in previous steps. Our hypothesis was that working memory capacity scores would predict complacency after we controlled for the influence of age. Since complacency is the assumption that automation is reliable, participants will depend on the automated aid when it is accurate or faulty. Thus, we can infer complacent behavior from targeting accuracy for reliable trials (i.e., high accuracy when dependent) and unreliable trials (i.e., low accuracy when dependent). Additionally, we can observe complacent behavior through targeting time because faster selections with unreliable trials compared to reliable trials suggest less time spent verifying faulty automation. We created an 'objective' measure of complacency by subtracting unreliable trial performance from reliable trial performance (i.e., separate for time and accuracy). Higher difference scores indicated greater dependence on automation. The difference scores for time and accuracy were standardized, so that both variables were on the same scale. Then, we added the scores together to create a combined complacency value. Participants in our study were more complacent with a higher DOA, so we investigated the role of working memory on complacency only for decision automation.

Separate regressions were conducted for decision automation complacency and complacency potential (Table 5 & 6). Each step in the model tested the extent to which a variable accounted for significant variance in subjective and objective measures of complacency after another variable was controlled for. Total variance accounted for is shown at R^2 and the new variance accounted for after adding another variable is indicated by ΔR^2. In Step 1, age was entered as a control variable. Age accounted for only 0.9% of the variance in complacency for decision automation. However, age predicted complacency potential by accounting for 15.5% of the variance in the subjective ratings. This finding was expected because of the significant age difference in complacency potential between younger and older adults.

Table 5
Summary of Hierarchical Regression Analysis Predicting Decision Automation Complacency

Variable	R^2	ΔR^2	β	ΔF	p

Step 1		.009	.009		0.75	.39
	Age			-.096		
Step 2		.022	.013		1.06	.41
	Age			-.036		
	Working Memory Capacity			.130		

Note. Bolded items indicate significant increments/predictors. The R^2 indicates the total variance accounted for with the inclusion of each step. The ΔR^2 indicates the change in total R^2 attributable to the inclusion of a step. The ΔF statistic indicates the change in F associated with the inclusion of each block of variables.

After we controlled for age, working memory capacity scores failed to account for significant unique variance in subjective or objective measures of complacency. The overall model for complacency potential was significant after including working memory, but the amount of unique variance was low (2.2%). Working memory was expected to predict complacency for decision automation, but our analyses suggest that participants had limited complacency in the automated task.

Table 6
Summary of Hierarchical Regression Analysis Predicting Complacency Potential

Variable		R^2	ΔR^2	β	ΔF	*p*
Step 1		.155	**.155**		14.64	**.00**
	Age			.393		
Step 2		.177	**.022**		2.14	**.00**
	Age			.472		
	Working Memory Capacity			.169		

Note. Bolded items indicate significant increments/predictors. The R^2 indicates the total variance accounted for with the inclusion of each step. The ΔR^2 indicates the change in total R^2 attributable to the inclusion of a step. The ΔF statistic indicates the change in F associated with the inclusion of each block of variables.

DISCUSSION

The purpose of this study was to examine the effect of age and DOA on complacent behavior in an automated task. Based on previous research, we hypothesized that older adults would depend more on automation with greater working memory demand than younger adults. Several interesting findings emerged from this study, many of which were contrary to our hypotheses:

1) Older adults experienced greater working memory demand for information automation. Younger adults experienced the same working memory demand for information and decision automation.
2) Task accuracy was the same for younger and older adults at each DOA. However, younger adults completed the targeting task quicker than older adults.
3) Participants' working memory capacity scores did not predict greater dependence on automation.

These findings are now discussed in more detail along with theoretical proposition for why these results may have occurred.

The two DOAs used in the study did vary in working memory demand, but only for older adults. We confirmed that decision automation required fewer cognitive resources than information automation. This finding supports the suggestion that higher forms of automation reduce cognitive demand (Onnasch et al., 2014). However, younger adults did not experience differences in working memory demand between information and decision automation. Researchers previously found that younger adults' working memory capacity does not predict performance in automated tasks (Saqer, de Visser, Emfield, Shaw, & Parasuraman, 2011). Since younger adults have greater working memory capacity, they have more resources to deal with varying levels of working memory demand.

In the automated targeting task, participants were expected to make more accurate and faster responses when using decision automation compared to information automation. This hypothesis was supported for targeting accuracy and response times. Our findings conform to a previous meta-analysis that showed performance increases for higher DOAs (Onnasch et al., 2014). Additionally, we hypothesized that younger adults would outperform older adults on targeting task accuracy and time. There were age differences in targeting time; older adults were significantly slower at making selections compared to younger adults. These differences in completion time were due to age-related changes in perceptual speed (Salthouse, 1985) and the additional time given to older adults to attempt each trial (i.e., 10 more seconds than younger adults).

The anticipated age difference in targeting accuracy was not found in the study. Participants of either age group did not significantly differ in selecting the correct choice when presented with information or decision automation. One potential explanation of this finding was that the lack of age differences in targeting accuracy could have been due to a speed-accuracy tradeoff. Each age group experienced a different amount of time pressure, which can influence decision-making (Payne, Bettman, & Johnson, 1993). Since older adults had 10 additional seconds for each trial than younger adults, they could have prioritized accuracy over speed to identify the correct answer for each trial. However, we found that there were no significant positive relationships between task accuracy and time for older adults except with unreliable decision automation. Even though older adults' accuracy and response times were positively related for those unreliable trials (*r* = .37), we observed the same positive relationship among younger adults as well (*r* = .26). Additionally, older adults on average completed all trials of the targeting task approximately 10 or more seconds before the time limit (i.e., 20 seconds). Older adults did not use all of the time allotted and failed to outperform younger adults (Tables 3 & 4). Based on our observed findings, it appears that a speed-accuracy tradeoff is not a suitable explanation.

The study tested the hypothesis that older adults would have greater complacency than younger adults for information automation and no differences in complacency for decision automation. Ho, Wheatley, and Scialfa (2005) suggested that age differences in working memory capacity increased automation dependence for older adults. Our results suggest that there were no age-related differences in complacency when the task varied in working memory demand. Overall, working memory capacity failed to predict complacency in the automated task. Similar to age differences in working memory, older adults had significantly higher complacency potential than younger adults. However, these attitudes did not translate to differences in automation dependence. Interestingly, Ho, Wheatley, and Scialfa (2005) found no age differences in complacency potential using the CPRS, but detected greater automation dependence among older adults. Even though the CPRS has high internal consistency and test-retest reliability, researchers only found a modest relationship (*r* = .42) between performance measures of complacency and individual differences in complacency potential (Singh et al., 1993a; Singh et al., 1993b).

Due to the mixed results observed across studies, the CPRS may not be a consistent indicator of actual complacency.

Our findings do not disprove the role of working memory in automation-induced complacency. Researchers have attributed lower working memory capacity to greater automation dependence (Ho, Kiff, Plocher, & Haigh, 2005; Ho, Wheatley, & Scialfa, 2005; Rovira, Pak, & McLaughlin, accepted with revisions). However, the simulation tasks used in our research failed to replicate the age-related differences in automation use found within the literature (Mouloua, Smither, Vincenzi, & Smith, 2002; Parasuraman & Manzey, 2010).

One major limitation of our study was the low task load (i.e., difficulty) in the targeting task, which kept constant the number of units within the grid. When researchers manipulated task load, younger and older adults differed in automation use (McBride, Rodgers, & Fisk, 2011). Even though the UAV simulation divided attention across two different tasks, participants could perform the targeting task without the automation. The grid was present at all times, so that participants could verify the automation. Older adults were as complacent as younger adults with automation that had greater working memory demand. Research that used the same UAV simulation tasks found higher complacency as task load increased, especially for participants with lower working memory (Rovira, Pak, & McLaughlin, accepted with revisions). This result supports the suggestion that complacency is only expected to appear under conditions of high task load (Parasuraman, Molloy, & Singh, 1993). Since we did not manipulate the task load of the targeting task, we failed to observe any age-related differences in automation use. Future research should examine the relationship between age and task load on human-automation interaction.

Participants engaged with only two forms of automation multiple times in our repeated measures design. Since performance was averaged across several blocks of trials, younger and older adults may have adjusted their behavior to the automation throughout the study. Recent aging literature found that older adults take longer to alter their dependence on automation, but these age-related differences in dependence are eventually mitigated (Sanchez, Rogers, Fisk, & Rovira, 2014). In our study, we had participants complete all trials using one DOA before presenting the other DOA. Future research may consider alternating between different forms of automation to vary working memory demand throughout the entire task.

Another possible limitation of our study is that participants did not perform the tasks without the use of automation (i.e., manual control). Researchers have used manual control as a way to investigate the benefits and costs of automation (Onnasch et al., 2014). The lack of automation support can demonstrate differences in task performance between automation conditions. Manual control represents a baseline to compare against low and high DOAs. Future research should include a manual control condition to examine age differences in automation use.

For our study, we attempted to create an objective measure of complacency that could explain the relationship between working memory and automation dependence. In the automation literature, researchers observed complacency as poor monitoring ability (i.e., accuracy) and the speed of responses to automation failures (i.e., response time)

(Parasuraman & Manzey, 2010). Thus, we combined response time and accuracy into a single measure. However, we failed to observe large differences between reliable and unreliable trial performance in our sample. In particular, targeting accuracy for unreliable trials did not decrease when participants used decision automation. Researchers observed a consistent connection between higher DOAs and poorer performance with unreliable automation (Onnasch et al., 2014). In our study, participants' improved accuracy for both reliable and unreliable trials with decision automation suggests little evidence for complacent behavior. Therefore, the lack of complacency in the automated task explains the small amount of explained variability from working memory capacity scores. Future research on automation dependence should assess and determine the conditions that increase the amount of measurable complacent behavior.

The simulation tasks used in the study were not entirely representative of real life situations. Similar to military scenarios, the tasks were designed to have time pressure that forced participants to make quick decisions. However, there were no penalties for making mistakes in the targeting or communication tasks. The penalty for taking a long time to respond or answering incorrectly could be deadly in actual military situations. Higher costs or values associated with making an error can reduce dependence on automation (Ezer, Fisk, & Rogers, 2008). Since the simulation tasks did not penalize participants for mistakes, younger and older adults were more complacent with our automation than other real world systems.

Our study differed from most automation studies in that we had participants perform a task where automation was always present. We decided to use automation that was visible at all times because we thought it would allow us to judge the effects of varying amounts of computerized support on complacency. In comparison, alarm-based systems are primarily high forms of automation (i.e., display a single automation recommendation). Also, alarm-based studies compare performance when the automation is present or not (i.e., reliance and compliance). The automation in our study allowed us to examine user dependence on reliable and unreliable systems that were always present.

Conclusions

The results of the study show that younger and older adults did not significantly differ in complacent behavior across two separate DOAs. Working memory capacity was not found to predict complacency even after controlling for differences in age. Thus, individual differences in working memory capacity did not affect dependence on automation when the aid varied in working memory demand. Low task load in the UAV simulation may have reduced age-related differences in complacent behavior. Further research is needed to examine the age-related effects of complacency for automation that varies in cognitive demand.

Practical Implications

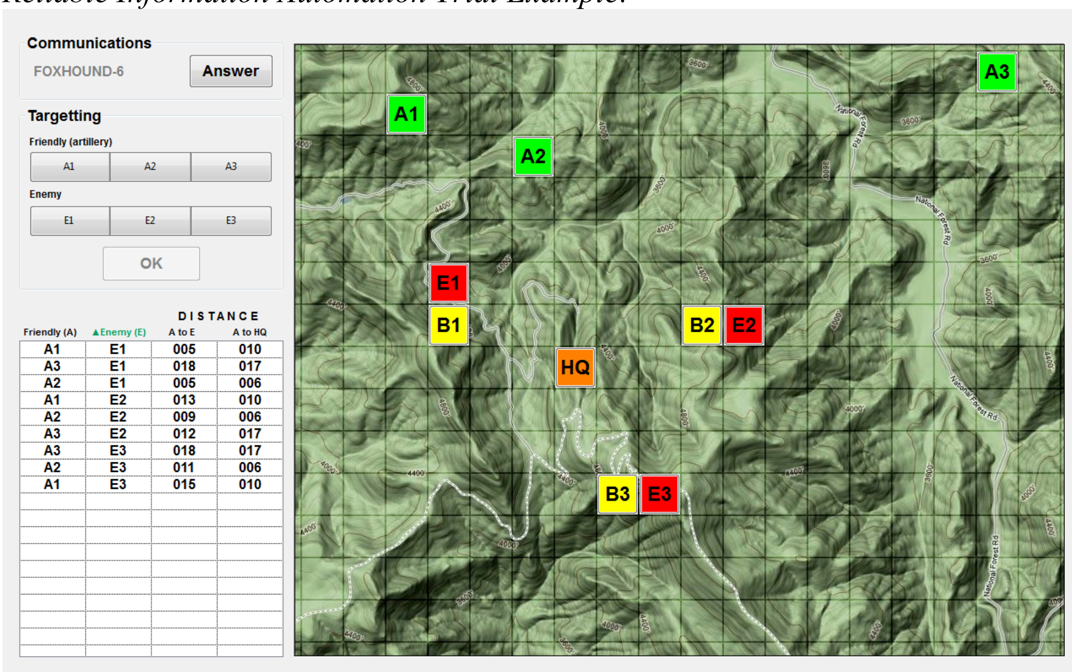
Examining the factors that affect automation dependence with novel interfaces can provide information about existing theories on automation use. Automation that is imperfect can influence how operators perform under varying amounts of computerized assistance. Our results indicated that younger and older adults did not differ in their dependence on automated aids that varied in working memory demand. However, both age groups were more complacent with greater automated support that had less working memory demand. Many automated devices and interfaces are designed to alleviate cognitive demand by providing fewer decision-making options for users (e.g., GPS, ATM). Since complacent behavior is more likely to occur with these types of technology, systems that utilize both higher and lower DOAs (i.e., adaptive automation; Corso & Moloney, 1996) could limit overdependence. Automation could occasionally provide less support to keep the user engaged in the task and cognizant of possible system failures. Therefore, our results suggest that designers should create interfaces that vary in working memory demand. Future research should examine the effect of adaptive automation that switches between differing levels of working memory demand on complacent behavior.

APPENDICES

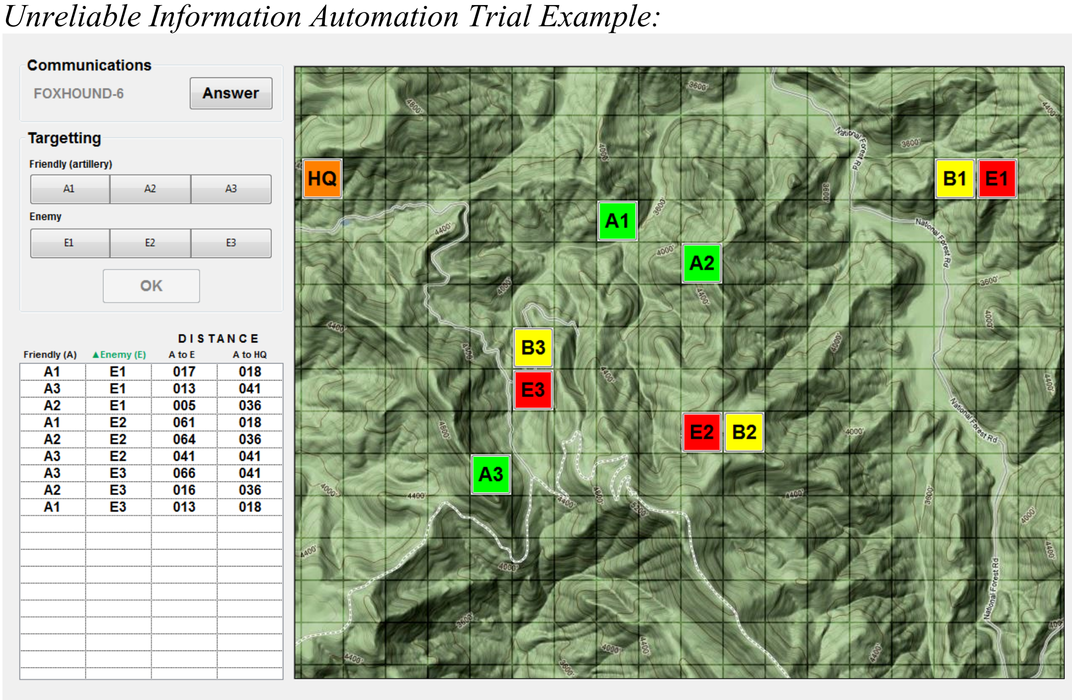
Appendix A

Examples of DOA and Reliability Manipulations

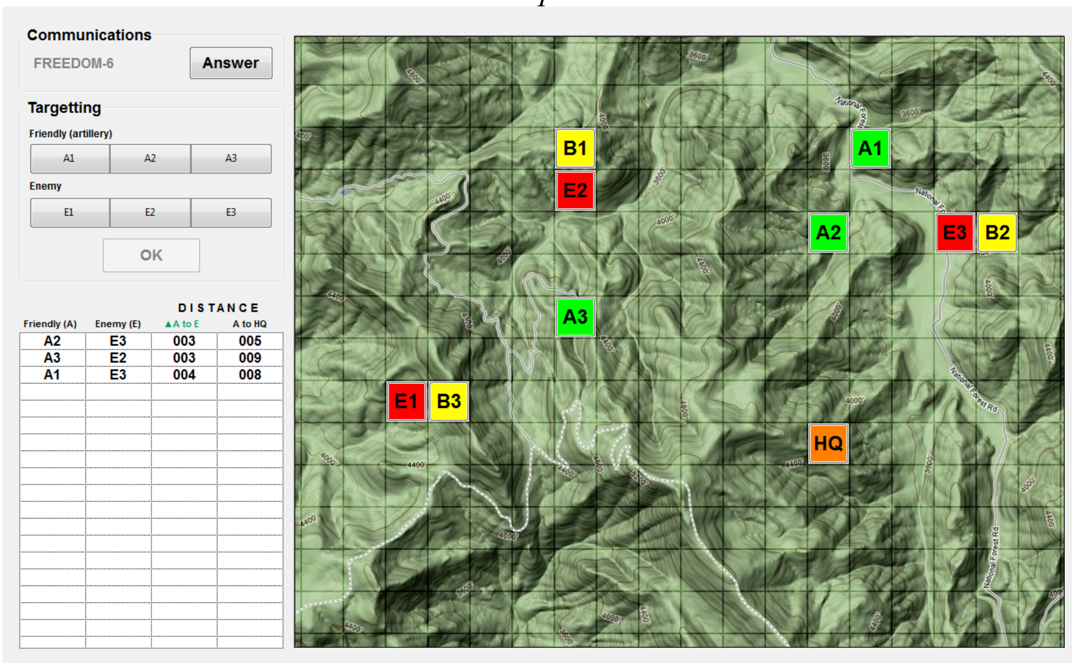
Reliable Information Automation Trial Example:



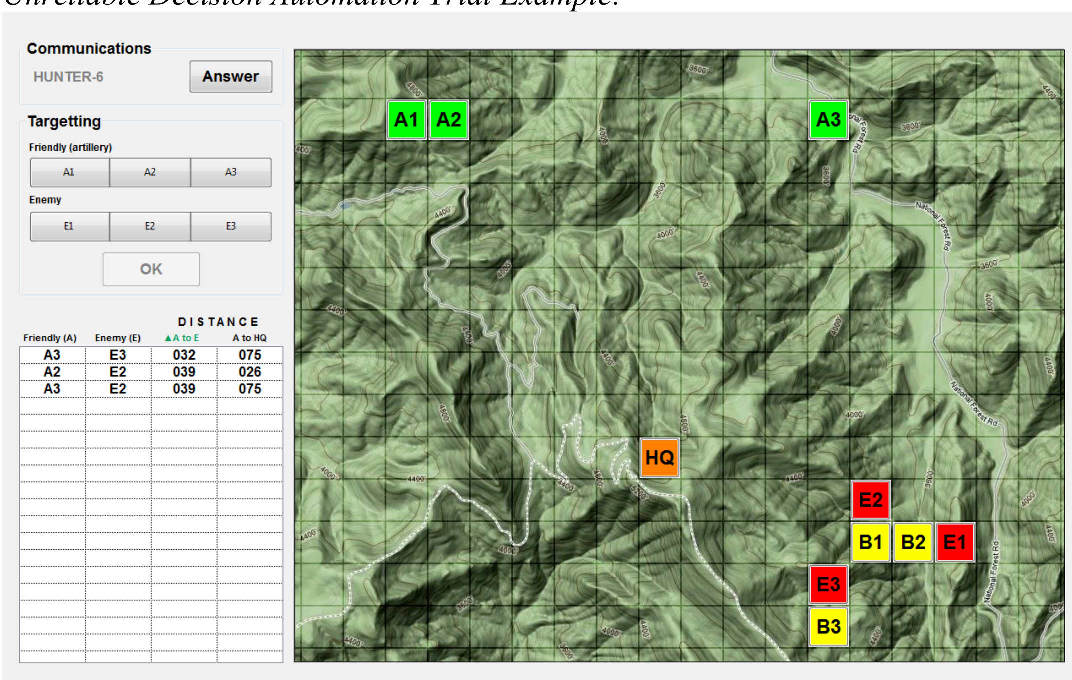
Unreliable Information Automation Trial Example:



Reliable Decision Automation Trial Example:



Unreliable Decision Automation Trial Example:



Appendix B

Automated Operation Span Task (Adapted from Unsworth et al., 2005)

Phase 1: Directions for Letter Memorization Practice Phase

- In this experiment, you will try to memorize letters you see on the screen while you also solve simple math problems.
- You will begin by practicing the letter part of the experiment.
- For the practice set, letters will appear on the screen one at a time. Try to remember each letter in the order presented.
- After 2-3 letters have been shown, you will see a screen listing 12 possible letters.
- Your job is to select each letter in the order presented. To do this, use the mouse to select each letter. The letters you select will appear at the top of the screen.
- When you have selected all of the letters, and they are in the correct order, hit the DONE box at the bottom right of the screen.
- If you make a mistake, hit the CLEAR button to start over.
- If you forget one of the letters, click the ? (question mark) button to mark the spot for the missing letter.
- Remember, it is very important to get the letters in the same order as you see them. If you forget one, use the ? button to mark the position.
- Do you have any questions so far? When you’re ready, click the button below to start the letter practice.

Phase 2: Directions for Mental Math Practice Phase

- Now you will practice doing the math part of the experiment. A math problem will appear on the screen like this: (2 * 1) + 1 = ?
- As soon as you see the math problem, you should compute the correct answer. In the above problem, the answer 3 is correct.
- When you know the correct answer, you will click the OK button with your mouse.
- You will see a number displayed on the next screen, along with a button marked TRUE and a button marked FALSE.
- If the number on the screen is the correct answer to the math problem, click on the TRUE box with the mouse. If the number is not the correct answer, click on the FALSE box. For example, if you see the problem: (2 * 2) + 1 = ? and the number on the following screen is 5 click the TRUE box, because the answer is correct. If you see the problem: (2 * 2) + 1 = ? and the number on the next screen is 6 click the FALSE box, because the correct answer is 5, not 6. After you click on one of the boxes, the computer will tell you if you made the right choice,
- It is VERY important that you get the math problems correct.
- It is also important that you try and solve the problem as quickly as you can.
- Do you have any questions? When you're ready, click the mouse to try some practice problems.

Phase 3: Directions for Combined Letter Memorization and Mental Math Phase

- Now you will practice doing both parts of the experiment at the same time. In the next practice set, you will be given one of the math problems.

- Once you make your decision about the math problem, a letter will appear on the screen. Try and remember the letter.
- In the previous section where you only solved math problems, the computer computed your average time to solve the problems.
- If you take longer than your average time, the computer will automatically move you onto the next letter part, thus skipping the True or False part and will count that problem as a math error.
- Therefore, it is VERY important to solve the problems as quickly and as accurately as possible.
- After the letter goes away, another math problem will appear, and then another letter.
- At the end of each set of letters and math problems, a recall screen will appear. Use the mouse to select the letters you just saw.
- Try your best to get the letters in the correct order. It is important to work QUICKLY and ACCURATELY on the math. Make sure you know the answer to the math problem before clicking to the next screen.
- You will not be told if your answer to the math problem is correct. After the recall screen, you will be given feedback about your performance regarding both the number of letters recalled and the percent correct on the math problems.
- During the feedback, you will also see your percent correct for the math problems for the entire experiment.
- It is VERY important for you to keep this at least at 85%.

- For our purposes, we can only use data where the participant was at least 85% accurate on the math.
- Therefore, you must perform at least at 85% on the math problems WHILE doing your best to recall as many letters as possible.

Appendix C

Subjective Trust in the Automated Aid (Adapted from Lee & Moray, 1992)

To what extent did you trust (i.e. believe in the accuracy of) the automation aid in this scenario?

Not at all | Extremely

To what extent did you rely on (i.e. actually use) the automation aid in this scenario?

Not at all | Extremely

To what extent were you self-confident that you could successfully perform without the automation aid in this scenario?

Not at all | Extremely

To what extent do you think the automation improved your performance in this scenario compared to performance without the automation?

Not at all | Extremely

Appendix D

General Rating of Trust in Automation (Adapted from Jian et al., 2000)

Below are several statements about the targeting aid that you just used (referred to as the "system").

Please rate your feelings about the aid from "not at all" to "extremely" (click one of the 7 buttons in a row for each question).

1. The system is deceptive

1 Not at all	2	3	4	5	6	7 Extremely

2. The system behaves in an underhanded manner

1 Not at all	2	3	4	5	6	7 Extremely

3. I am suspicious of the system's intent, action, or outputs

1 Not at all	2	3	4	5	6	7 Extremely

4. I am wary of the system

1 Not at all	2	3	4	5	6	7 Extremely

5. The system's actions will have a harmful or injurious outcome

1 Not at all	2	3	4	5	6	7 Extremely

6. I am confident in the system

1 Not at all	2	3	4	5	6	7 Extremely

7. The system provides security

1 Not at all	2	3	4	5	6	7 Extremely

8. The system has integrity

1 Not at all	2	3	4	5	6	7 Extremely

9. The system is dependable

1 Not at all	2	3	4	5	6	7 Extremely

10. The system is reliable

1 Not at all	2	3	4	5	6	7 Extremely

11. I can trust the system

1 Not at all	2	3	4	5	6	7 Extremely

12. I am familiar with the system

1 Not at all	2	3	4	5	6	7 Extremely

Appendix E

Complacency Potential Rating Scale (Adapted from Singh, Molloy, & Parasuraman, 1993a)

1. Manually sorting through card catalogs is more reliable than computer-aided searches for finding items in a library.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
2. If I need to have a tumor in my body removed, I would choose to undergo computer-aided surgery using laser technology because computerized surgery is more reliable and safer than manual surgery.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
3. People save time by using automatic teller machines (ATMs) rather than a bank teller in making transactions.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
4. I do not trust automated devices such as ATMs and computerized airline reservations systems.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
5. People who work frequently with automated devices have lower job satisfaction because they feel less involved in their job and those who work manually.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
6. I feel safer depositing my money at an ATM then with a human teller.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
7. I have to record an important TV program for a class assignment. To ensure that the correct program is recorded, I would use the automatic programming facility on my recording device rather than manual taping.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
8. People whose jobs require them to work with automated systems are lonelier than people who do not work with such devices.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
9. Automated systems used in modern aircraft, such as the automatic landing system, have made their journey safer.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
10 ATMs provide a safeguard against the inappropriate use of an individual's bank account by dishonest people.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
11. Automated devices used in aviation and banking have made work easier for both employees and customers.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
12. I often use automated devices.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
13. People who work with automated devices have greater job satisfaction because they feel more involved than those who work manually.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
14. Automated devices in medicine save time and money in the diagnosis and treatment of disease.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
15. Even though the automatic cruise control in my car is set to a speed below the speed limit, I worry when I pass police radar speed-trap in case the automatic control is not working properly.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
16. Bank transactions have become safer with the introduction of computer technology for the transfer of funds.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
17. I would rather purchase an item using a computer that have to deal with the sales representative on the phone because my order is more likely to be correct using the computer.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
18. Work has become more difficult with the increase of automation in aviation and banking.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
19. I do not like to use ATMs because I feel that they are sometimes unreliable.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree
20. I think that automated devices used in medicine, such as CAT scans and ultrasound, provide very reliable medical diagnosis.	Strongly Agree	Agree	Undecided	Disagree	Strongly Disagree

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