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International Journal of Industrial Ergonomics 34 (2004) 175–186
International Journal of Industrial Ergonomics
www.elsevier.com/locate/ergon

Measurement of trust in complex and dynamic systems using a quantitative approach

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Received 19 February 2004; received in revised form 26 March 2004; accepted 29 March 2004

Abstract

In highly automated inspection systems today, humans act in a supervisory capacity, i.e., monitoring the process during normal operations and intervening to take manual control when necessary to override faulty automation. Research has concluded that the intervention behavior of supervisors is based on their trust in the automation. However, several problems remain with the current trust paradigm, the most important ones concerning the ambiguity and inaccuracy of the data. An original theoretical framework relating machine properties to operator perceptions is needed. To achieve this framework, machine properties need to be mapped to these perceptions through the development of quantifiable dimensions, referred to as uncertainty. Uncertainty, unlike trust, can be easily quantified and, therefore, can be related to system properties. This research attempts to measure uncertainty using a Line Length Experiment Module that simulates a real-life automated system monitored by an inspector. The experiment tests the ability of a human inspector to identify defects relative to the machine's ability to do so, rather than trying to gauge their competencies separately and subsequently comparing them. Three levels of uncertainty, established using National Institute of Standards and Technology (NIST) guidelines, were administered in the experiment, with the users rating their trust at each level through questionnaires. The results showed that the overall trust in the system had a significant inverse relationship with the system uncertainty. Hence, the performance of hybrid systems can be improved by decreasing uncertainty, an improvement that will have an impact on quality.

Relevance to industry

Trust of humans in machines is important in the performance of hybrid systems. Increasing this trust will improve overall system performance of systems.

Keywords: Trust; Automation; Hybrid systems; Uncertainty; Competence

1. Introduction

Automated and hybrid inspection systems have become increasingly common in the manufacturing industry. In these systems, humans assume less

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0169-8141/$ - see front matter
doi:10.1016/j.ergon.2004.03.005

direct control of the physical process, becoming instead supervisors of the automated process, i.e., monitoring performance during normal operations and intervening to take manual control when necessary to override faulty automation. If the operator either overrides the automation too frequently or is too hesitant to take manual control, system performance will be compromised with potentially disastrous consequences. Clearly, in such an environment, the operator's moment-to-moment allocation of functions is a critical decision-making process, one that is important for us to understand and optimize. Unfortunately, it is very difficult to predict the intervention behavior of the supervisor. Although many models have been proposed to describe this behavior, no one theory has emerged to explain and predict intervention behavior completely. Previous research (e.g., Sheridan, 1988; Muir, 1989) hypothesizes that the intervention behavior of supervisors is based on their trust in the automation. Case studies conducted by Zuboff (1988) provide some support for this hypothesis.

Recent work on trust in machines has been essentially drawn from the earlier work on trust between humans (e.g., Muir, 1994), with researchers studying trust both in process–control systems (Sheridan, 1988; Lee and Moray, 1992; Muir and Moray, 1996; Jian et al., 2000; Bisantz, 2001) and in a wide variety of complex automated systems such as air traffic control (Masalonis, et al., 1998; Masalonis and Parasurman, 1999) and anti-aircraft warfare (Jian, et al., 2000). Their findings indicate that trust, or its lack, in machines significantly affects operator performance.

In automated systems the process involved is so complex that there will always be properties the supervisors will never know. If the automation fails in an area outside their knowledge base, supervisors will fail to detect the fault and, as a result, fail to override the automation. Since supervisors understand that they can never have complete knowledge of the properties of automation, they are aware that it may fail in unforeseen and potentially disastrous ways, while at the same time realizing it must be used most of the time. Hence, supervisors cannot base their allocation behavior on the properties of automation alone. This allocation decision is further complicated by individual differences, the disparity that individuals themselves bring to the situation (Muir, 1994).

In addressing supervisory action in the face of incomplete knowledge of the system and the individual differences in the use of automation, we must determine the intervening variable that mediates between automation and supervisor response to it. Experts in the field of supervisory control (Sheridan and Hennessy, 1984) have suggested that trust is this mediating variable. A typical example can be seen in the work place where supervisors let subordinates do their jobs without intervention to the extent of the trust between them. The supervisory control of personnel bears a close resemblance to the supervisory control of automation (Sheridan and Hennessy, 1984), suggesting that our natural use and understanding of trust can be applied to "automated subordinates" as well. Developing a theory that describes human trust in machines and explains how this trust changes with experience will allow for the prediction of the allocation decisions of supervisors. Such a theory could also be used to identify problems in the decision process and suggest solutions, preventing the consequences of incorrect allocation decisions (Muir, 1994).

1.1. Existing approaches to the measurement of trust

Various models, originally developed to examine trust between people, have been applied in recent years to the human/machine relationship. Research from both social science and engineering viewpoints agree that trust is a multidimensional concept, reflecting a set of interrelated perceptions and actions of a human (Bisantz et al., 2000). Although this idea of trust has been defined in many ways in psychological literature, most of these definitions are either too narrow or too vague to be tested, or fail explicitly to acknowledge its multidimensional nature (Muir, 1994).

Deutsch (1958) posited that trust included two concepts: motivational relevance and expectation. In developing the concept of expectation more fully, Rotter (1967) defined trust in terms of the expectancy on the part of one individual or group that the statement of another individual or group can be relied on. Recognizing the multidimensional character of trust, Barber (1983) defined it in terms of taxonomy of three specific expectations: persistence, technical competence and fiduciary responsibility (Table 1). According to Barber, the expectation of persistence is the foundation for trust: expecting something to work in a predictable way reduces complexities by limiting possible outcomes. Equally important is the expectation of technical competence, especially central to the meaning of trust in automation (Muir and Moray, 1987). Barber has related technical competence to the Rasmussen's (1983) theory of knowledge-based, rule-based and skill-based behavior. For example, supervisors may expect a human-controlled machine to be competent in performing lower level routine tasks but not in handling unusual system states. This perception of the competence of the machine would affect the level of trust in it: a supervisor would afford a higher level of trust for the routine tasks and less trust for the more difficult ones. The third dimension of trust in Barber's model, fiduciary responsibility which deals with expectations that people have moral and social obligations, is not germane to the human–machine relationship.

Rempel et al. (1985) have specifically applied the concept of trust and expectation to the human–machine relationship, developing a model that defines trust in hierarchical stages, with the trust at any one stage based on the outcome of the preceding one. According to their model, predictability dominates early in the relationship, followed by dependability and faith. This model indicates that humans will judge the predictability of an automated system by evaluating the consistency and desirability of its recurrent behavior. This assessment of predictability is based on three major factors: the actual predictability of the machine's behavior, the operator's ability to estimate the predictability of the machine's behavior, and the stability of the environment in which the system operates.

The variance in machine performance from time to time plays an important role in assessing its predictability. The lower the variance in machine performance, the greater the predictability. In addition, the ease with which the behavior of the machine can be observed is important: a transparent system whose behavior can be easily observed and understood cultivates trust because its functional relationships are accessible and clear. Finally, the machine's predictability also depends on the environment in which it operates. Operators may distrust a machine if it does not operate in a predictable manner because of changes in the environment. Hence, operators must learn to distinguish such situations so as not to distrust the machine because of apparent unpredictability due to environmental changes.

As the relationship progresses, dependability, the understanding of the stable dispositions that guide the partner's behavior, becomes an important basis for trust, determining the extent to which a system or a machine is reliable. This leap of faith, as suggested by Rempel et al. (1985), requires humans to go beyond the behavioral evidence generated by a machine and integrate

Table 1
Barber's Model of Trust

Expectation	Impact	Description
Persistence	Provides basis for all other forms of trust.	The foundation of trust that establishes a constancy in the fundamental moral and natural laws.
Technical competence	Supports expectations of future performance based on capabilities, knowledge or expertise.	The ability of the other partner to produce consistent and desirable routine performance, technical facility and expert knowledge.
Fiduciary responsibility	Extends the idea of trust beyond that based on performance to one based on moral obligations and intentions.	The expectation that people have moral and social obligations to hold the interest of others above their own.

their past experiences based on its predictability and dependability. Therefore, in order to develop faith in any particular machine, the human supervisor must be well versed with it, meaning that a period of time is required for faith to develop.

Muir (1994), seeing the possibilities of both Barber (1983) and Rempel et al. (1985), combined these two to develop a more comprehensive model of trust in automation. While Barber's model provides the broader context and richness of meaning needed to characterize the many interactions in a complex supervisory task, Rempel et al.'s provides the dynamic factor needed to predict how trust may change as a result of experience with a system. Muir (1994), suggesting that these two models were orthogonal to each other, defined a new one, taking into account the dimensions of both. Muir's integrated model of human trust in automation crosses Barber's (1983) taxonomy of trust as rows with Rempel et al.'s (1985) taxonomy as columns (Table 2).

Muir and Moray (1996) conducted two experiments to examine operator trust and the use of automation in a simulated supervisory task. The first experiment examined the nature and dynamics of human trust in machines. The second tested the relationship between the properties of automation, trust and human intervention. These studies found that a subjective rating from an operator could be used to predict and optimize the dynamic allocations of function in an automated system (Muir and Moray, 1996). Master et al. (2000), using the model developed by Muir (1994) and the components of trust suggested by Barber (1983) and Rempel et al. (1985), developed a subjective rating instrument, a trust questionnaire, to determine the effects of the level of trust an operator has in an automated system. This questionnaire was used as part of this research (Table 3).

1.2. Limitations of existing approaches—need for a quantitative approach

Despite the research into trust measurement, several problems remain with the current trust paradigm. First, quantifiable system properties are being characterized by personifications prone to misinterpretations and error. Since an operator would know what functions the machine is intended to perform, a better approach may be to assess the important machine properties or functions directly. For example, one of the functions of a machine vision system is to identify correctly nonconforming components; the performance measure in this instance would be a proportion. Under the proposed approach, the operator's assessment of the machine's ability to perform this function would also take the form of a proportion, which, in effect, is a perception or estimate of the actual proportion. Such a proportion has the added advantage of being definitive both in a linguistic and mathematical sense, giving

Table 2
Muir's Model of trust

Expectation	Basis of expectation at different levels of experience		
	Predictability (of acts)	Dependability (of dispositions)	Faith (in motives)
Persistence			
Natural Physical	Events conform to natural laws	Nature is lawful	Natural laws are constant
Natural Biological	Human life has survived	Human survival is lawful	Human life will survive
Moral Social	Humans and computers act decently	Humans and computers are inherently good and decent	Humans and computers will continue to be good and decent in the future
Technical Competence	*j*'s behavior is predictable	*j* has a dependable nature	*j* will continue to be dependable in the future
Fiduciary Responsibility	*j*'s behavior is consistently responsible	*j* has a responsible nature	*j* will continue to be responsible in the future

Table 3
Trust questionnaire

Competence: To what extent does the system perform a given task effectively?

1 Strongly disagree — 7 Strongly agree

Predictability: To what extent can you anticipate the system's behavior with some degree of confidence?

1 Strongly disagree — 7 Strongly agree

Reliability: To what extent is the system free of errors?

1 Strongly disagree — 7 Strongly agree

Faith: To what extent do you have a strong belief and trust in the system to do a particular task effectively for which there may be no proof?

1 Strongly disagree — 7 Strongly agree

Overall Trust: To what extent do you trust the system overall?

1 Strongly disagree — 7 Strongly agree

What percentage of responses by the system do you think are correct?

0 %

the benefit of increased clarity. The proposed quantitative approach, then, has the potential of solving what Muir (1994) sees as the "confusing terminology in the study of trust."

Second, the perceptions of machine properties are measurements, usually taken by humans who are imperfect measuring instruments, especially at estimating parameters of numerical, as opposed to attribute, data. The current dimensions of trust are subject to similar limitations since they are typically derived from surveys that employ Likert scales. To address this issue, the operator in the proposed research will be treated as a measuring instrument. The extent to which this approach can be adapted to a subjective set of dimensions is limited since the exact trustworthiness of a particular machine, for example, cannot be quantified. However, determining the actual characteristics of a machine, such as the proportion of defective items correctly identified, is feasible in a controlled setting.

Third, beliefs regarding self-competence are frequently inaccurate. There is evidence that the difference between an operator's trust in a machine to perform a particular function and her/his self-confidence to perform the same function determines intervention behavior (e.g., Moray et al., 2000). In light of the errors related to both the perceived expertise of the operator herself/himself and the properties of machines, this research proposes that a relative measure may be more accurate than the difference between two absolute ones. In this approach, for example, an operator would be asked to compare his or her ability to identify defects relative to the machine's ability to do so, rather than trying to gauge these competencies separately and subsequently comparing them.

Fourth, trust may not be the best measure of an operator's perceptions of machine properties. It has been shown that experience with machines does not always influence trust and that overall hybrid system performance is not always directly related to this dimension (Lewandowsky et al., 2000). Indeed, it is conjectured that the explanation for the apparent paradoxes reported by Lewandowsky et al. (2000) is that the level of uncertainty remained constant in both instances. For example, if the probability of a correct determination is given as 0.99; then, the measure of uncertainty, represented in this instance by the variance, is equal to 0.0099 (since for a Bernoulli random variable $\sigma^2 = (1-p)p$). On the other hand, the variance would be identical if the probability of an incorrect determination was 0.99; hence, the uncertainty is symmetric, so to speak. It is conjectured that any decision or action would be the same in both instances, despite the diametric circumstances. The uncertainty is greatest when the probability of a correct determination, or equivalently an incorrect one, is equal to 0.5, which, in effect, is the same as flipping a coin. Accordingly, this research proposes to find an explicit measure of uncertainty as an alternative to trust.

2. A quantitative approach for measurement of trust

The main purpose of this research is to improve overall system performance in a hybrid environment, i.e., one in which the supervisor has complete knowledge of both the functions of the machine and its competence in executing them. An original theoretical framework relating machine properties to operator perceptions is needed. To achieve this, machine properties need to be mapped to the perceptions through the development of quantifiable dimensions relating these properties directly. Obtaining these quantifiable dimensions requires the development of an alternative measure to trust, referred to as uncertainty, because it, unlike trust, can be easily quantified and, therefore, related to system properties.

2.1. Definition of uncertainty

For the purposes of this study, the broad definition of uncertainty, one that includes a large number of uncertain situations, proposed by Zimmermann (2000) is used: "Uncertainty implies that in a certain situation a person does not dispose about information, which quantitatively and qualitatively is appropriate to describe, prescribe or predict deterministically and numerically a system, its behavior or other characteristic." This definition is appropriate for our study as we are looking to obtain a quantifiable measurement for trust, focusing on a human-related subjective interpretation of uncertainty that depends on the quality and quantity of information available to the human. To understand and quantify uncertainty clearly, the depiction in Fig. 1 from Zimmermann (2000) is used.

Fig. 1 depicts the phenomenon about which human judgments are to be made. Information or data emitted by a complex and dynamic system includes such impulses as noise, visible data such as displays, or measurable properties like temperature. The observer does not directly perceive this information but rather obtains it with a degree of uncertainty that can be measured using different models, one example being probability distributions. Hence, the observer perceives the information about a phenomenon only after it has been filtered through the uncertainty theory exemplified by the model being used (Zimmermann, 2000).

The prominent causes of uncertainty are lack of information, abundance of information, conflicting evidence, ambiguity and measurement. For the purposes of this study, the only cause of uncertainty in the system will be the measurement.

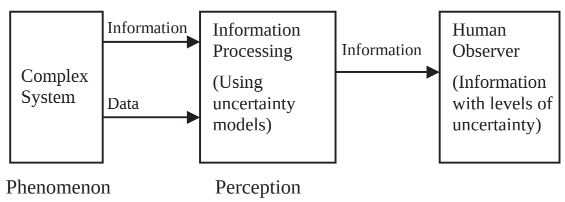

Fig. 1. Uncertainty perception.

2.2. Quantifying uncertainty using NIST guidelines

The uncertainty in the system can be quantified using such uncertainty models as standard National Institute of Standards and Technology (NIST) guidelines, probability theories, fuzzy set theories, and interval arithmetic. To reduce complexity, the guidelines for the expression of uncertainty in measurement formulated by the NIST are used to express how uncertainty is quantified and understood in this research. Each component of uncertainty, however evaluated, is represented by an estimated standard deviation, termed a standard uncertainty with suggested symbol u_i, equal to the positive square root of the estimated variance u_i^2.

2.3. Evaluating the uncertainty component

For example, an input quantity X_i whose value is estimated from n independent observations $X_{i,k}$ of X_i is obtained under similar conditions of measurement. In this case the input estimate x_i is usually the sample mean:

$$x_i = \overline{X_i} = \frac{1}{n}\sum_{k=1}^{n} X_{i,k} \tag{1}$$

and the standard uncertainty $u(x_i)$ associated with x_i is the estimated standard deviation of the mean:

$$u(x_i) = s(\overline{X_i}) = \left[\frac{1}{n(n-1)}\sum_{k=1}^{n}\left(X_{i,k} - \overline{X_i}\right)^2\right]^{1/2}. \tag{2}$$

If the system depends on only one parameter, then Eq. (2) can be considered as the uncertainty in the system.

3. Methodology

The experiment was conducted using 12 subjects drawn from a population of graduate and undergraduate students at Clemson University between the ages of 20 and 30. The experiment was conducted using Gateway 3000 Personal Computers with a Windows XP Operating Systems and a Pentium IV Processor. The viewing screen was a 17-in color monitor used at a resolution of 800×600 pixels, and the subject observed the screen from a distance of approximately 500 mm. Each subject used a mouse to respond to the stimulus material.

The experiment simulated a real-life automated system for which the inspector has to judge its performance using stimulus material consisting of a Line Length Experiment Module written in Visual Basic 6.0. Each screen had a standard reference line that was fixed in length and position, and a variable line that was randomly generated and positioned within a specific area (Fig. 2). The system classified the variable line in comparison with the reference line as either very very short, very short, short, long, very long or very very long. The subjects visually compared lengths of the variable and reference lines. Based on their perception and the system's classification, the subject either agreed or disagreed with the system (Fig. 2).

A randomized complete block design was used in the study to control for subject-to-subject variability. The factorial experiment consisted of three levels of uncertainty nested within two different mean error levels. The order of the 6 treatment combinations was randomized for each subject.

The subjects were asked to complete a consent form and a demographic questionnaire before starting the experiment. A training session and a pilot study were conducted prior to the main experiment. The experiment was conducted on a single day with breaks given to the subjects between sessions.

3.1. Training session

1. *Initial overview:* The subjects were introduced to the Line Length Experiment Module and were shown typical screens of the experiment.
2. *Classification of variable lines:* The six classifications of the variable line were explained to the subjects using an interactive training session that helped subjects identify the lengths of the six variable lines.
3. *Error in the system:* For each variable line, the response of the system could be any one of the

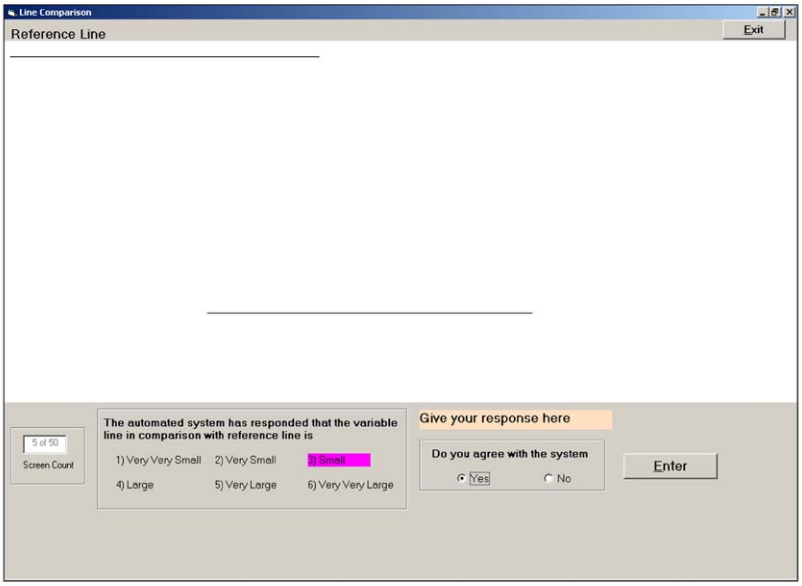

Fig 2. Typical snapshot of the experiment.

six classifications. Each classification is associated with a magnitude of error in the system. The severity of the errors was also provided to the subjects.

4. The trust questionnaire and its terminology were explained to the subjects.

3.2. Pilot study

After the training session, 6 subjects were used in a pilot study to establish the experiment protocol. Four sets of 50 screens were used to evaluate and set the uncertainty levels for the experiment. Four levels of uncertainty—1.0, 1.5, 2.0 and 2.5—were used in this pilot study with the mean of the errors kept constant at 1 for each set. An error of 1 denoted a 5% difference in length of the reference and variable lines, while errors of 2, 3, 4 and 5 denoted 10%, 15%, 20% and 25% differences in length, respectively. The results of this pilot study showed that the trust components were more strongly related to the number of incorrect responses in a set than to the uncertainty of the set as a whole. This finding resulted in keeping the number of incorrect responses constant for the main experiment, as the effect of uncertainty was the purpose of the study. Since the subjects' perceptions of the line length was as expected, the same line lengths were used in the main experiment.

3.3. Main experiment

Six sets of 50 screens were presented to the subjects in the experiment. Each set had the same number of incorrect responses, i.e., 25 screens in each set of 50 screens. Because, the number and kind of errors were preset for the 6 sets of 50 screens that provided three levels of uncertainty for mean value 1—1.00, 1.25, and 1.50—and three for mean value 2—2.00, 2.25 and 2.35. The order of the 50 screens in a set, as well as the order of the 6 sets, was randomized for each subject to control for order effects. After each set of 50 screens, the subjects responded to the trust questionnaire, rating their trust in the system. The experiment was conducted in an unpaced mode since the effect of pacing was not examined in this study. The methodology was designed to achieve the following objectives:

- To relate machine properties of the system to a quantifiable dimension referred to as uncertainty.
- To examine the relation between uncertainty and the trust in the system.
- To examine the relation between uncertainty and the other trust components.
- To examine the relation between the mean of errors and the trust in the system.

3.4. Data collection

Data were collected on the responses given by the subjects for each screen. The subjects either agreed or disagreed with the system by responding "Yes" or "No" for each screen. In addition, the responses to the trust questionnaires were recorded. The subjects rated each subjective measure on a scale of 1–7 and estimated the percentage of correct responses for each set of 50 screens on a scale of 1–100.

4. Results

The subject's responses for each screen and the trust questionnaire were analyzed. Components of the trust questionnaire included competence, predictability, reliability, persistence and overall trust. For each trust component, Hartley's F-Max test ($S^2_{\max}/S^2_{\min} = 1.653 < F_{\max} = 1.67$) was used to check the homogeneity of data across the two means. Shapiro–Wilks test proved that the data collected was normally distributed. For each component, analysis of variance (ANOVA) was performed separately for each mean value to determine if the individual components were related to uncertainty. A combined analysis was performed for each component to compare the overall results for mean values 1 and 2.

The results showed that competence was significantly affected by varying the uncertainty for both mean value 1 ($p = 0.0012$) and mean value 2 ($p < 0.0001$). In addition, there was a difference in competence for mean values 1 and 2 ($p = 0.0532$). Single degree-of-freedom comparisons were used to compare uncertainty levels for each mean value using level 1 as the reference level. These comparisons showed a significant statistical difference between the competence means except for uncertainty levels 1.00 and 1.25 for mean value of 1 (Fig. 3).

The analyses for reliability, persistence and predictability showed no significant effect of uncertainty level for either mean value or for the overall comparison of mean values 1 and 2.

The ANOVA for overall trust showed a significant effect of uncertainty level for mean values 1 and 2 ($p < 0.0001$ and $p = 0.0470$, respectively), but the two mean error levels were not different. The linear contrasts for mean value 1 showed significant differences between the means of overall trust for uncertainty levels, but the uncertainty level 2 was not significantly different from level 1 for mean value of 2. These results also indicate an inverse relation between trust and uncertainty (Fig. 4).

The percentage correct was set at 50% for all levels of uncertainty and mean values, and the subjects were asked to estimate the percentage correct after completing each set of 50 screens. For mean value 2, the subjects' estimates for percent correct were excellent (52%), while there was an overestimate (62%) for mean value 1.

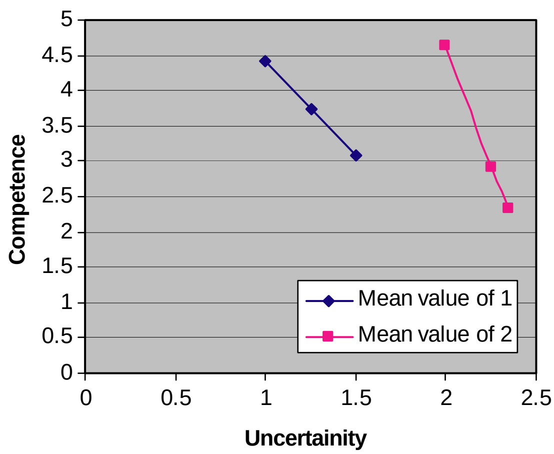

Fig 3. Plot of competence vs. uncertainty for mean values of 1 and 2.

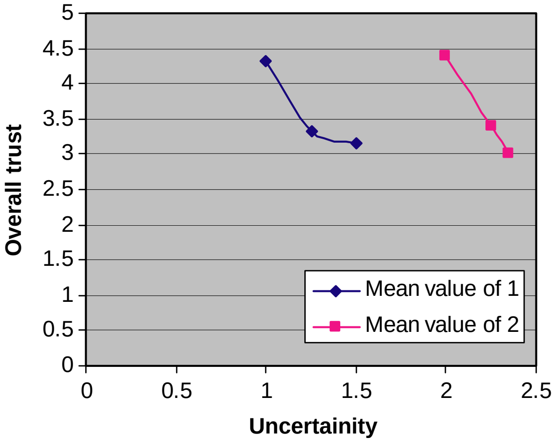

Fig 4. Plot of overall trust vs. uncertainty for mean values of 1 and 2.

Table 4
Subjects' response ratio

Error	Yes	No	Percentage "No" responses
0	1386	414	33
1	225	183	44.85
2	99	297	75
3	10	182	94.19
4	8	336	97.67
5	0	468	100

System errors ranged from 1 (5% difference in length of reference and variable lines) to 5 (25% difference in length), and a summary of subjects' response for each system error is presented in Table 4. The percentage of "No" responses increased with error severity and was 100% for an error of 5.

5. Discussion and conclusions

While research has shown that trust plays a significant role in influencing operator strategy for automated systems (Lee and Moray, 1992), it has been determined that overall hybrid system performance is not always directly related to this construct (Lewandowsky et al., 2000). For this type of system, an operator needs to know what functions the machine is intended to perform in order to assess the machine's properties directly. Studies conducted by Muir and Moray (1996) have shown that subjective rating of the operator could be used to predict and optimize the dynamic allocations of function in automated system. Therefore, this research assessed machine properties using the quantifiable dimension of "uncertainty," and data on the measurement of trust was collected using the questionnaire developed by Master et al. (2000).

As the results indicate, competence was the only dimension that was strongly related to uncertainty of the system. A strong inverse relation was found, i.e., an increase in uncertainty led to a decrease in competence. As none of the other trust components were related to uncertainty, it can be concluded that a competent system is a less uncertain one.

The other three dimensions of trust are predictability, reliability and persistence. Predictability was not found to be related to the uncertainty of the system, probably due to the random order used at each uncertainty level for each subject. Uncertainty may have had an effect on this component if screen order had been maintained for each subject. Reliability, a direct measure of number of errors in the system, showed no effect on trust, probably because the number of incorrect responses was kept constant for each treatment. The last component of trust considered, persistence to achieve a goal at each level of uncertainty, cannot be substantiated as the 50 screens for any given level were randomized for each subject, not allowing them to perceive any pattern for any level of uncertainty. Hence, the results showed no relationship between persistence and uncertainty. These components of trust may be a function of the overall error mean and the number of errors rather than of uncertainty alone. However, before any definitive conclusions can be drawn, further studies under different conditions are needed.

The findings of this experiment indicated that overall trust behaved similarly to competence. It also showed a significant inverse relation with uncertainty, meaning that as the level of uncertainty in the system increases, the trust in the system decreases. In addition, it behaved similarly to competence at the different uncertainty levels, suggesting that competence may be an important dimension in the development of trust in a system.

This study addressed some of the limitations of the existing approaches in the measurement of trust by comparing the operator's ability to identify defects relative to the machine's ability to do so and revealed that uncertainty could be used to assess the machine properties of the system directly. A strong inverse relation between uncertainty and competence shows that a competent system is one that is less uncertain, a conclusion further supported by the finding that overall trust and uncertainty in the system are also inversely related. This result is significant because in automated systems if the uncertainty of the machine is decreased, the trust of human in the automation increases, thereby enhancing the performance of hybrid systems, an improvement that has a direct impact on quality.

This experiment, however, is just the first step in quantifying uncertainty and its relationship to trust. Future research is needed to study the effect of different levels of uncertainty on trust for only two mean error levels. The effect of mean number of errors on trust could be better evaluated if more levels were studied. Also, as the number of uncertainty levels was limited to 3, an attempt to quantifiably relate uncertainty to the trust components was not undertaken. A better approach would be to include more number of levels of uncertainty to relate uncertainty and the trust components with equations. The uncertainty of a system can be quantified in a number of other ways including probability theories, fuzzy set theories, and interval arithmetic. Studies using different approaches could be conducted to determine the best technique for quantifying uncertainty as a system property. Trust and its components appear to depend on three factors: the mean of the number of errors, the uncertainty of the errors and the number of errors. Studies establishing trust as a function of these three factors should be conducted.

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