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Analysing and Modelling Human Trust to a Navigation Robot

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***Abstract*—Human trust plays a crucial role in Human-Machine Interactions (HMIs) within autonomous systems. This paper delves into the factors that influence human trust in machines, including varying error rates and types made by the machine, as well as the human's ability to intervene and rectify errors. To explore these factors, we conducted three scenarios involving a simulated claw robot navigating through multiple objects to detect and locate a target object. The first scenario examined the effect of changing error rates on human trust in the machine. In the second scenario, we investigated how variability in speed and accuracy of reaching the target impacted human trust. Lastly, we explored whether human trust in the machine changed when individuals had the capability to intervene and correct severe errors made by the machine. We then proposed a regression model to estimate human trust. Our results showed that human trust is significantly affected by changes in error rates. Our participants reported a higher trust on robot with low speed but higher accuracy in performing the task than the robot with high speed but lower accuracy. Interestingly, the ability to intervene and correct the robot's errors improved the participants' trust in the robot. Our regression result showed that we can estimate trust using different type of errors committed by machine which can be applied in real world scenarios.**

***Index Terms*—human-machine interactions (HMIs), error rates, target identification, trust, computational modelling, machine or robot action perceptions**

I. INTRODUCTION

The concept of human trust in machines can have different interpretations and implications depending on the discipline or field of human activity. Trust holds distinct conceptual meanings in various contexts, such as interpersonal relationships, organizational dynamics, and interactions between humans and machines [1]–[3]. In addition, trust components can be dispositional, situational, and learned [2]. Dispositional trust is a trust component that is dependent on demographic such as gender or culture, whereas situational and learned trust are described as trust components that are dependent on time varying factors such as task difficulty, self-confidence, and experience [2].

Beyond these literal definitions, human trust in machines has been described by many authors as an essential factor that establishes team relationships between humans and their machine partners [3]–[8]. In a recent study, Aiken et al. demonstrated that understanding a robot's limitations, not its task intentions, can promote a user's assistance in maintaining a level of confidence and reliability on the robot [9]. However, the impact of a robot's errors or mistakes with respect to the nature of the task also has a significant effect on human trust in the robot [10]. A related research study has revealed that robot's sensitivity to its mistakes and its ability to apologize or recover from such mistakes can impact on human trust in the robot [11]. Furthermore, human perceptions of the severity of the robot's errors also have different level of influences on human trust in the robot [12]. While some individuals might consider specific errors to be severe and attach high importance to them under certain conditions, others may see the same errors as minor and attach less importance [12].

Recent studies investigated factors affecting human trust in machine in different scenarios. One of such examples was demonstrated by Ahmad et al. in a study to investigate the relationship between a humans' cognitive load, trust, and anthropomorphism during human-robot interaction. The authors created a "Matching the pair game" where the participant would play with one of two types of robot called the 'Husky' and 'Pepper' [13]. Pepper exhibited a humanoid appearance while Husky possessed machine like features. Their goal was to understand human trust in the robots, as a teammate, in a game-playing situation that demanded a high level of cognitive load. Using a humanoid versus robot paradigm, they investigated the impacts of physical anthropomorphism while testing the impacts of robots error rates on human trust to the robots. Their results demonstrated that there was an inversely proportional relationship between trust and cognitive load [14]. This result suggested that as the amount of cognitive load increased in the participants, the level of their trust decreased [13]. Interestingly, Husky was perceived as more trustworthy than Pepper when it was depicted as featuring a low error-rate teammate [14]. Conversely, the participants perceived that the Pepper robot was more trustworthy than the Husky robot when high error rates were featured [13].

In a related study, by Jung et al. the authors used an experiment with human-like features to investigate human trust in machine in non-reciprocal interactions. They developed six externally and internally machine agents in a decision making task where participants played a game with three human face agents and three robotic face agents with different risk taking personalities [14]. The agents' risk taking personalities were rated with different scores. The agents can present any of the scores as risk taking personality to the participant as a choice during the game. The participant would simultaneously play the game with the two agents and rate their level of confidence or trust in each of the agents (human face or robotic face) based on the the risk taking personalities presented by them at various stages during the game. Results from this study demonstrated that participants earned more trust in the agents with a human face than the agents with a robotic face [14]. Furthermore, Peter de Vries et al. also used a computer-based route planner to study the effects of errors on control allocation, the role of trust, and self-confidence in a domain route planning system. In this study, participants completed ten route-planning trials in manual mode, and ten in automatic mode [15]. Results from their analysis showed that having higher automation error rates yielded lower human trust in the system [15]. However, compared to the automatic mode, high manual error rates resulted in a less reduction in levels of self-confidence [15].

Errors committed by machines are common and cannot be underestimated in research relating to trust in human-machine interactions (HMI). Some errors can be perceived significant, capturing the user's attention and requiring attention to address them. However, certain errors may be minor and not raise any concerns for the user. Regardless of the severity of the errors, effective collaboration between machines and users relies on trust and understanding to achieve the desired goal. Humans can only trust partners they understand and believe in. Machine errors primarily depend on factors such as faulty algorithms and the complexity of the assigned tasks. Therefore, understanding the severity, causes, and occurrences of errors is crucial when investigating human trust in machines.

The possibilities of developing a generalized trust model for assessing human trust to machine across disciplines have been questioned and investigated by several researchers. Answers to these questions have not yielded the desired results because different individuals and organisations demand the use of autonomous machines for different reasons and specific purposes. To build effective trust relationships between humans and their machine partners, individuals or organisational needs must be factored into human machine trust relationships [3], [4]. This is important to avoid misuse and disuse of the system and foster harmonious working relationships between users of machines and their partners [4]. For instance, people who are not aware of the exact performance levels of their machine partners often experience a mismatch in expectations [3], [4]. Detecting this mismatch as it affects human trust in machine remains a fundamental issue that needs to be addressed. Research investigating human trust to machine according to industrial and organisational needs have not fully been explored and a lot more is still required in this area. Importantly, there is a need to conduct research within real-world scenarios, particularly in relation to autonomous systems [1].

Therefore, in this paper, we investigated factors affecting human trust in machine using a simulated robotic arm mimicking a factory machine navigating through multiple objects to detect and locate a target object. These factors include different error rates and error types committed by the robot as well as the ability of the human to intervene and correct the errors while performing the given task. We examined these factors in three scenarios each having a different number of runs. The details of the designed scenarios and blocks are described in the subsequent sections. Our aims are: firstly, to examine the effect of changing error rate on human trust to the machine. Secondly, to investigate how variability in speed and accuracy of reaching the target impacted human trust. Lastly, we explored whether human trust in the machine changed when individuals had the capability to intervene and correct severe errors made by the machine. We then proposed a regression model to estimate human trust.

II. Method

A. Participants

Ten adult participants at an average age of 27 years were recruited for this study. The study was approved by the Automatic Control and Systems Engineering ethics committee at the University of Sheffield. The participants provided written informed consent to attend the study. On arrival at the Lab, participants were asked to seat in front of a computer screen and told to observe the movements of a simulated robotic arm in a factory task. They were instructed to read and follow the instructions on the computer screen as they observe the task.

B. Task

To achieve the above mentioned aims, we designed an experiment mimicking a simulated robotic arm in a factory, navigating through different objects to identify and pick up a target object. As can be seen in Fig. 1, at the beginning of the task (run), the program automatically sets a blue ball as a target destination and the robotic claw appears a maximum distance of three red balls away from it. The aim of the robot would be to move towards the blue target ball, reach the target ball and grasp it.

In total, there are six possible movements that the robot can make; three correct and three incorrect movements. The movements are described as being correct if the robot arm moves towards a designated target location (i.e. MTT- Moved Towards Target), reaches the target location (i.e. TR- Target Reached), or identifies the correct target (i.e. CTI- Correct Target Identified), as can be seen in Fig 1. Consequently, the robot commits an error when it moves away from the target (i.e. Moving Away- MA), reach the target but steps off (i.e. Stepped Off the Target- SOT) or identifies or grasps any of the red balls which are the wrong target locations (i.e. Wring Target Identified- WTI). The robot's three correct and three incorrect movements can be seen in Fig 1.

The run finishes when the robotic claw grasps either the blue ball or one of the red balls. The robotic claw then resets for a new run or task to begin. This process is repeated until a set number of runs are completed. The claw executed about 105 runs through out the entire experiment. The program repeats for a maximum number of five runs before a participant can select a key, between 1 to 5 from the computer key board, to register his or her level of trust in the perceived actions of the claw. Keys 1 to 5 represent a scale of low, medium, and high level of trust respectively. For instance, a participant might select key 1 to mean he has low level of trust in his or her observed actions of the robot, or key 3 for medium-level trust, or 5 as high level trust as the case may be. This process is repeated until all the runs are performed and the participants finished observing the task in all the scenarios.

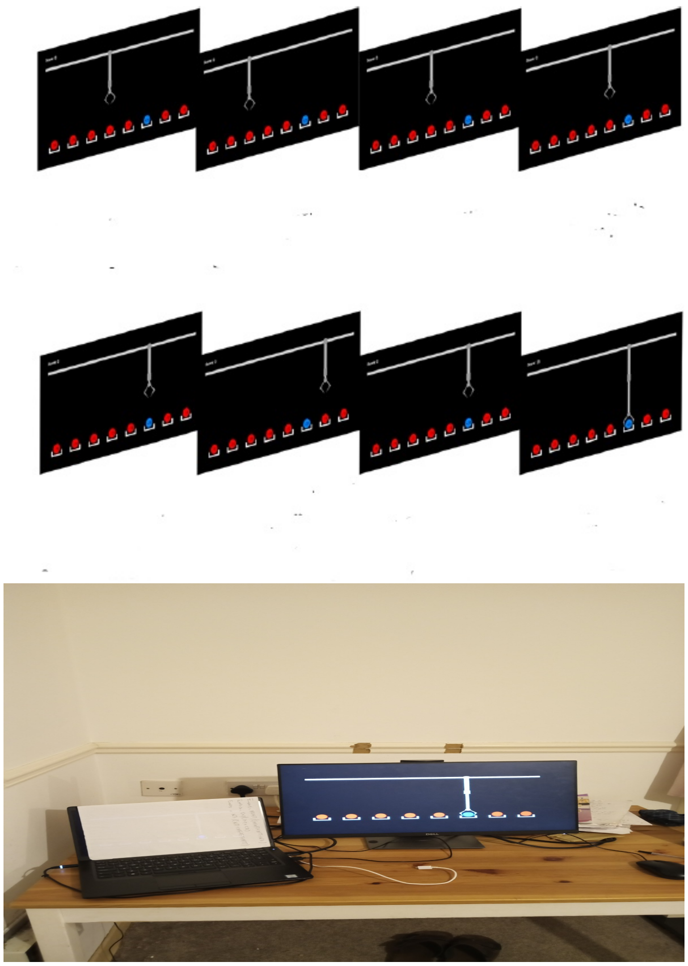

Fig. 1. Screen shots of the robotic claw performing the task in the experiment. The top 8 screenshots show an example of an experiment run, where the robot performs different correct and incorrect movements until it reaches the target.

C. Experiment

The experiment was conducted in a quiet room. The participants were asked to turn off their mobile phones to avoid distractions while attending to the experiment. As can be seen in Fig. 2, the experiment consisted of three scenarios, with three

TABLE I
PRESET ERROR RATE PROBABILITIES OF THE THREE TYPES OF ERRORS ACROSS THE THREE BLOCKS IN SCENARIO ONE

No. of Blocks	***MA Errors***	***SOT Errors***	***WTI Errors***
Block 1	***0.10***	***0.20***	***0.10***
Block 2	***0.25***	***0.20***	***0.10***
Block 3	***0.40***	***0.20***	***0.10***

blocks for the first scenario and two for the last two scenarios. Each participant observed a minimum number of six out of the seven blocks of the experiment. In total, all the participants completed 105 runs in the experiment. To avoid biasing their judgments, we did not inform them on how the experiment was designed or its aim. To make them focus their attention on the task, we told them to critically observe the robot's movements/actions by counting the number of observed errors. At the end of the experiment, important information about the claw movements and participant's reported levels of trust were recorded for further analysis according to our hypothesis.

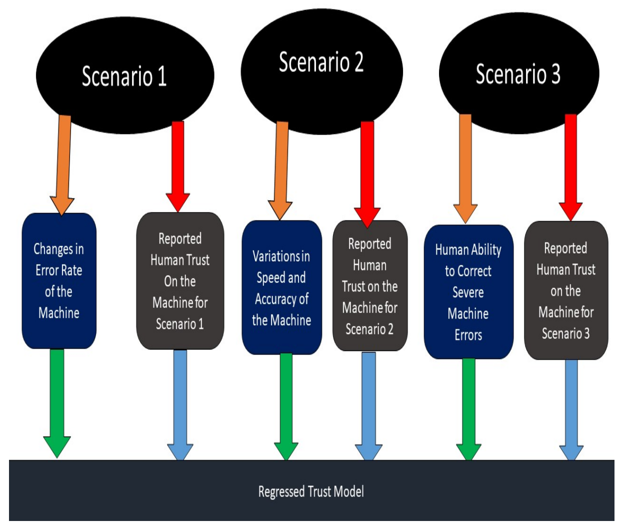

Fig. 2. Summary of experimental block flow diagram.

1) Scenario One: The goal of this scenario is to investigate how changing the error rates can affect the human trust in the machine. For this purpose, we designed three blocks of robot actions, each lasting 3 minutes. In this scenario, we set the probabilities of the MA errors as 0.10, 0.25 and 0.40 across the three blocks respectively and fixed the probabilities of SOT and WTI errors at 0.20 and 0.10 respectively. As earlier explained in the preceding section, the aim of this section is to see how variations in MA errors across different blocks could affect human trust to the machine. As can be seen in Table VI, we manipulated our design such that only MA errors vary across the blocks while SOT and WTI errors were set to occur at constant probability rates. This was to ensure that changes in the reported trust levels in the robot are as a result of changes in MA errors.

TABLE II
PRESET ERROR RATE PROBABILITIES OF THE THREE TYPES OF ERRORS ACROSS THE TWO BLOCKS IN SCENARIO TWO

No. of Blocks	*MA Errors*	*SOT Errors*	*WTI Errors*
Block 1	***0.30***	***0.30***	***0.10***
Block 2	***0.10***	***0.10***	***0.50***

TABLE III
PRESET ERROR RATE PROBABILITIES OF THE THREE TYPES OF ERRORS ACROSS THE TWO BLOCKS IN SCENARIO THREE

No. of Blocks	*MA Errors*	*SOT Errors*	*WTI Errors*
Block 1	***0.40***	***0.20***	***0.10***
Block 2	***0.40***	***0.20***	***0.10***

2) Scenario Two: Our goal here is to investigate changes in human trust in a machine when we alter the machine priority between speed and accuracy in identifying the target. The robot operates at low speed and high accuracy when the probability of MA error is high but the probability of SOT and WTI errors are low. On the other hand, the robot acts on a high speed but low accuracy when the probability of MA is low but the probability of the WTI and SOT errors are high. To achieve this, we defined two blocks of experiments, each three minutes long with the probabilities of the errors set as MA = 0.30, SOT = 0.30 and WTI = 0.10 in the first block, and the error probabilities set at MA= 0.10, SOT = 0.10 and WTI = 0.50 in the second block. The robot functions on low speed and high accuracy in the first block while in the second block, it operates on high speed but low accuracy. As can be seen in Table II, in the first block, we assigned WTI error to 0.10 to allow the robot to commit less of the WTI errors so that accuracy of correctly selecting the targets can be prioritized. In the second block, we changed the probability of WTI error to 0.50 to prioritize speed. We also increased the probabilities of MA and SOT errors from 0.1 to 0.30 in the second block to reduce the speed in reaching the target.

3) Scenario Three: Our goal in this scenario is to investigate the effect of allowing human intervention to change the machine's action on human trust in the machine. For this purpose, in this scenario, the participant can intervene each time the robotic claw commits WTI error by clicking a key on the computer keyboard. As a result, the run is paused and a text is displayed on the computer screen, acknowledging the participant's invention and asking the participant to press a key to allow the robot to perform another action. We used two blocks of errors and set the probability of errors in both blocks as MA = 0.40, SOT = 0.20 and WTI = 0.10. Here the same probabilities of errors are set in both blocks. In summary, compared to the first two scenarios, in the this scenario we allow participant(s) to correct WTI errors committed by the robot.

D. Error Rate Calculation

The error rates of the three types of errors across all the scenarios and blocks were calculated as follows:

$$\text{MA}_{rate} = \frac{\textbf{No}(\text{MA})}{\textbf{No}(\text{MA}) + \textbf{No}(\text{MTT}) + \textbf{No}(\text{WTI})}, \tag{1}$$

$$\text{SOT}_{rate} = \frac{\textbf{No}(\text{SOT})}{\textbf{No}(\text{SOT}) + \textbf{No}(\text{CTI})}, \tag{2}$$

$$\text{WTI}_{rate} = \frac{\textbf{No}(\text{WTI})}{\textbf{No}(\text{WTI}) + \textbf{No}(\text{MA}) + \textbf{No}(\text{MTT})}, \tag{3}$$

where $\textbf{No}(\text{X})$ denotes the number of errors for error (X). Following the experiment, we verified that the observed error rates in the experiment were consistent with the preset probabilities selected for each block.

E. Method of Analyses

To ensure that our analyses is in line with our design hypothesis, we recorded the reported trust from participants every one minute in each block across the three scenarios. We compared the average recorded trust values against error rates in each block. We also investigated if there are correlations between the average trust values and the error rates of the different types of errors across the blocks in all the scenarios.

To investigate how error rate would change human trust in the machine, we conducted Pearson correlation between average value of reported trust and MA errors obtained from scenario one.

To verify the impacts of speed or accuracy on human trust to the machine, in scenario two, we recorded average values of reported trust in the first and second blocks respectively and conducted paired t-test analyses to investigate the average difference between trust in the first and second block.

In scenario three, we conducted Pearson correlation analyses between average values of reported trust and WTI errors across all the blocks.

Finally, to develop a model that can estimate trust in all the three scenarios, we pooled together total number of reported trust from all the participants across all the three scenarios and regressed them with all the numbers of errors used for our analyses in each of the investigated scenarios.

III. RESULTS

A. Scenario One Results

TABLE IV
PEARSON'S CORRELATION RESULTS OF SCENARIO 1. N REFERS TO THE TOTAL NUMBER OF REPORTED TRUST VALUES ACROSS ALL PARTICIPANTS.

	MA Errors	*SOT Errors*	*WTI Errors*
Pearson Correlation (r)	***-.493*******	***-.057***	***.001***
p-value (2-tailed)	***.000***	***.585***	***.992***
N	***94***	***94***	***94***

To ensure that the MA errors vary significantly across the blocks while the SOT and the WTI errors do not, according to our experimental design, we conducted a paired t-test to compare the mean difference between the number of errors

TABLE V
PAIRED T-TEST RESULTS OF TRUST MEAN VALUES ACROSS THE BLOCKS IN SCENARIO 2

No.of Blocks	*MA*	*SOT*	*WTI*	*(Trust Mean)*	*S.E*
LS/HA (Block 1)	***0.30***	***0.30***	***0.10***	***3.38***	***0.263***
HS/LA (Block 2)	***0.10***	***0.10***	***0.50***	***2.50***	***0.327***

across all the blocks. As expected, our results showed significant differences between the mean values of the MA errors across the three blocks (p-value < 0.05). However,the mean values of SOT and WTI errors across all the blocks did not show any significant difference (p-value> 0.05).

Following the above-mentioned paired t-test results, we further investigated how the changes in MA affected trust in the robot. We pooled together the MA error rates in each one minute before the trust was reported, and performed Pearson's correlation analysis between reported trust values and MA values. Our results showed a significant negative correlation between number of MA errors and reported values of trust from all the participants, $r = -0.493$ and p-value < 0.001. This result explains that as the machine commits more of MA errors, participants trust to the machine decreases.

B. Scenario Two Results

To examine how speed or accuracy can affect human trust in the machine, we conducted a paired t-test analysis to compare the mean values of reported trust between block one (the low speed but high accuracy condition) and block two (where the machine exhibited high speed but low accuracy in getting to the target). Our results showed, on the average, that participants experienced significantly higher trust in the robot with lower speed but higher accuracy than the robot with higher speed but lower accuracy. For the low speed but high accuracy block, the mean value of reported trust was 3.38, and standard Error (SE) was 0.263, whereas the high speed but low accuracy block recorded a mean trust of 2.50,and standard error of 0.327,($t(7) = 2.966$, p-value < 0.05).

This result further tells us that participants had a significantly higher trust in the robot when it maintains low speed but high accuracy than when the robot is very fast to execute the task but commits a lot of mistakes. To investigate which error type(s) contributed to changes in reported trust across the blocks, we pooled together all the reported values of trust and all values of WTI errors in the two blocks and performed Pearson's correlation analysis between trust and WTI errors. Our results showed again that WTI errors had a significant negative correlation with reported trust across the two blocks,($r = -.481$, p-value $= 0.001$).

We performed Pearson's correlation analysis between trust against MA and SOT errors across the two blocks. Our results did not show any significant correlation between trust values and values of MA and SOT errors respectively, p-values> 0.05. This result tells us that even though the robot committed other types of mistakes like the MA and the SOT errors, WTI errors was the one contributing significantly to the changes in human trust in the robot.

C. Scenario Three Results

TABLE VI
PEARSON'S CORRELATION RESULTS OF SCENARIO 3

	MA Errors	*SOT Errors*	*WTI Errors*
Pearson Correlation	***.133***	***.451***	***-.434***
Sig. (2-tailed)	***.599***	***.060***	***.072***
N	***18***	***18***	***18***

To investigate human trust to the robot in human's ability to correct the most important errors of the robot, we performed Pearson correlation analysis between trust and WTI errors for six participants who completed scenario three. Four of the participants did not participate in this part of the experiment. Unlike scenario two, our results showed that there is no significant relationship between reported values of trust and values of WTI errors, p-values > 0.05. This result illustrates that WTI errors have no significant impact on human trust on the robot if human can correct them. It may further suggest that humans regained their trust in the robot as a result of their ability to successfully collaborate with the robot to jointly achieve a setup goal to a logical end.

D. Estimating Human Trust Using Regression Analysis

Following the results of our correlation analysis between reported values of trust and different error rates in all the scenarios, we pooled all the values of error rates from scenarios one and two, and regressed them with actual values of reported trust across both scenarios. Our regression result showed that we can estimate trust using MA and WTI errors respectively (F3, 43) = 8.084, (B1 = -5.515, B3 = -3.507, t = 10.474, p-value <0.001), R^2 = 0.361.

However, the rate of the SOT errors is not significantly correlated with trust, p-value>0.05. This result is as expected, as the rate of SOT errors did not show, in our correlation results, any significant relationship with trust in all the scenarios.

IV. CONCLUSION

According to our study, human perceptions of machine behaviour differ from person to person. Our results also suggest that human trust is significantly affected by changes in error rates. For example, changes in rates of the MA errors in case scenario one had a significant negative correlation with reported trust values, while SOT and WTI errors which rates are relatively constant did not exhibit any significant relationship with reported trust values. In addition, this result reveals that participants had higher trust on robot with low speed but higher accuracy in performing the task than the robot with high speed but lower accuracy. Furthermore, our results did not show any significant correlation between mean values of trust and error rates when humans intervened to correct severe errors (WTI) committed by the robot. In other words, the ability of participants to correct severe errors of the robot increased their trust or confidence on the robot's ability to successfully carry out the task.

Finally, in this study, our research focus was on human trust behaviour in response to different erroneous actions of machine. However, we did not investigate the variations in trust value across participants and/or over the time. In future, it would be interesting to use physiological signals, such as brain signals, to measure trust in machine more accurately, objectively and continuously.

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