Objective and Subjective Responsibility of a Control-Room Worker

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Abstract— When working with AI and advanced automation, human responsibility for outcomes becomes equivocal. We applied a newly developed responsibility quantification model (ResQu) to the real world setting of a control room in a dairy factory to calculate workers’ objective responsibility in a common fault scenario. We compared the results to the subjective assessments made by different functions in the diary. The capabilities of the automation greatly exceeded those of the human, and the optimal operator should have fully complied with the indications of the automation. Thus, in this case, the operator had no unique contribution, and the objective causal human responsibility was zero. However, outside observers, such as managers, tended to assign much higher responsibility to the operator, in a manner that resembled aspects of the “fundamental attribution error”. This, in turn, may lead to unjustifiably holding operators responsible for adverse outcomes in situations in which they rightly trusted the automation, and acted accordingly. We demonstrate the use of the ResQu model for the analysis of human causal responsibility in intelligent systems. The model can help calibrate exogenous subjective responsibility attributions, aid system design, and guide policy and legal decisions.

Keywords— Intelligent systems, Decision support systems, Human–computer interaction (HCI), Cognitive Engineering

I. INTRODUCTION

Artificial intelligence (AI) and advanced automation have become part of finance and banking (e.g., algorithmic trading and automatic credit approvals), transportation (e.g., autonomous vehicles), medicine (e.g., advanced decision support systems, and medical robotics), industry (e.g., automated production facilities and control rooms), and other domains. In these systems, computers and humans share information collection and evaluation, decision-making and action implementation.

When interacting with intelligent systems, human responsibility becomes equivocal. For example, what is the human responsibility when all information arrives through a system that collects and analyzes data from various sources, without the human having any independent information? The determination of the human causal responsibility is particularly important in the design and investigation of intelligent systems that can lead to injury and even death, such as autonomous vehicles or automated control systems in industry that involve hazardous materials.

To date, the subject of human responsibility was investigated mostly from philosophical, ethical, moral or legal perspectives, but much less from cognitive engineering perspective of human interaction with intelligent systems.

Numerous philosophical and legal studies investigated different facets of the concept of responsibility [1-3]. When humans interact with intelligent systems, role responsibility refers to the specific roles and duties assigned to the humans, for which they are accountable to others. However, this role assignment does not specify the causal association between the human actions and the overall outcomes. This relation is defined by causal responsibility, which describes the actual human contribution to the outcomes and consequences.

The ability to control a system and the resulting consequences is a necessary condition for attributing causal responsibility [4]. As the level of system intelligence increases, there is a shift towards shared control, in which the human and computerized systems jointly make decisions or control actions [5]. There may also be supervisory control, in which the human sets high-level objectives, monitors the system and only intervenes if necessary. In intelligent systems, with artificial intelligence, machine-learning and neural networks, developers and users may not be able to fully control or predict all possible behaviors and outcomes, since internal structures can be opaque (“black box”) and can occasionally produce peculiar and counterintuitive results [6,7]. Subsequently, humans may no longer be able to control intelligent systems sufficiently to be rightly considered fully responsible for their outcomes [8-12], and the intelligent system (or its developers) may share some of the responsibility [13,14]. This difficulty to determine human responsibility with intelligent systems leads to a “responsibility gap” in the ability to divide causal responsibility between humans and systems [9,15,16].

In addition, there is a demand to involve humans in automated processes in a manner that will facilitate “meaningful human control” [17]. However, simply adding a human into the loop does not assure that the human will have meaningful control. There may be cases when the human cannot supervise the system adequately, or when the human has to make decisions, based exclusively on input from automated functions that one cannot evaluate independently [18]. Currently, there are different, and at times conflicting interpretations and policies regarding meaningful human control, and system designers lack models and metrics to analytically address this issue [19].

To bridge the responsibility gap, we developed a theoretical Responsibility Quantification model (ResQu model) of human responsibility in intelligent systems [20], to enable us to divide causal responsibility between the human and the intelligent system. Using information theory, we defined a quantitative measure of causal responsibility, which is based on the characteristics of the operational environment, the system and...
the human, and the function allocation between them. The ResQu responsibility is defined as the expected share of the unique human contribution to the overall outcomes. This measure can also be used to quantify the level of meaningful human control, based on the ground that meaningful human control requires the human to have some causal responsibility for the outcomes. The ResQu model is a normative theoretical model that computes the optimal level of responsibility, a rational human should adopt. However, in reality, people may act non-optimally when they interact with intelligent systems [21-26]. In a second study, we analyzed the descriptive abilities of the ResQu model to predict actual human behavior in controlled laboratory interactions with an automated decision aid [27]. We showed that the ResQu model can also serve as a descriptive model for predicting actual human responsibility or human perceptions of their own responsibility. The results also showed a systematic tendency to attribute more responsibility to another person than to oneself, in the same situation, in a manner that resembles aspects of the “fundamental attribution error” in social psychology [28-30].

In the current study, we expand the research by applying the ResQu model to a real-world setting. To do so, we examined a fault scenario in a control room of a cheese-making factory (dairy). We calculated the objective ResQu responsibility measure for the control room worker, in the selected scenario, and compared the results to subjective assessments of the operator's responsibility, made by different functions in the diary.

II. THE PRODUCTION PROCESS AND FAULT SCENARIO

The factory is a cheese making factory (dairy) located in Israel. The plant produces cheeses of various kinds, 24 hours a day, every day of the week - excluding Saturday. The production line includes a milk pasteurization system, a pipe system that transports milk and milk products between different production stations, 30 large containers for storage of incoming milk from milk farms, other tanks for storage of different substances (milk sub-products, or cleaning materials), a large number of automatic packaging machines, and cooling systems operating on heat exchangers. Also installed is a cleaning system that is connected to each of the milk storage containers, which is used to wash and clean the containers and the pipe system when a container is emptied from milk, before new milk can be pumped into the container.

All processes in the production and storage systems are controlled from a single control room. The control room is run 24-hours a day by an operator and a shift supervisor, in two 12-hours shifts. Workers in the control room are required to ensure that the processes are carried out properly and have to intervene in fault situations. To do so, they use a computerized control system, which displays the factory's piping and instrumentation diagram (P&ID), including the states of various containers, pipes, taps, milk flow sensors, temperatures, and various alerts that indicate technical faults that require the operator's intervention. In case of such an alert, the operator (with the assistance of the shift supervisor) is the one responsible for selecting the correct response, which is then carried out by the automated control system. Selection of an incorrect action, in case of a fault scenario, can lead to substantial losses. The duties of the operator and the shift supervisor are not limited to interactions with the automated control system. They are also responsible for the manual connections of pipes between the milk delivery trucks that arrive during the day and the milk containers, physically checking various faults, alerted by the control system, informing maintenance personnel on technical issues, and more. Thus, there are times in which they operate under high workload, or during which one of them has to leave the control room.

For the current study, we selected a rather common fault scenario in which there is a malfunction in a container-mounted sensor, which is used to alert that the container is empty of milk and needs to be rinsed and cleaned. In normal operation, each container has periods, along the day, in which it contains milk (to produce various dairy products) and periods when it is empty (from the time the milk runs out to the moment it is refilled with new milk). Before refilling with new milk, the container needs to be cleaned. A container-mounted sensor activates an indication in the control room’s P&ID display, stating that a certain container is empty. Upon such an alert, the control room operator should initiate container cleaning, by pressing a button that starts an automatic flushing process with cleaning material. When this process is complete, the container can be refilled with milk. The container-mounted sensor sometimes suffers from an electrical short, that disables its ability to detect the presence of milk. This malfunction causes the automated system in the control room to falsely present an alert, indicating that the container is empty. Note that due to the physical nature of the sensor’s operation, it is not possible for the sensor to falsely present that there is milk in an empty container. This fault scenario is not rare, and according to factory data, it occurs on average once a month, in one of the 30 milk containers.

In the above fault scenario, if the operator complies with the alert and presses the automatic flushing button, detergents are pumped into the container, ruining all the remaining milk. Usually, after about 5 minutes, the operator’s mistake is detected, as the cheese production line will start to release green colored milk product, which are mixed with detergents, and the production line workers will alert the control room operator to stop the milk flow from the container. On the other hand, there could be cases in which the operators might suspect that the alert is false, for example, if the operators remember that only a short time ago, they filled the specific container with newly arriving milk, so it is therefore unlikely that the container is empty. If this is the case, the operator can go to the specific container and physically examine whether it still has milk. To do so, the operator leaves the control room for about 15 minutes, goes to the container area, climbs a ladder to the top of the container, opens the top lid and examines the milk level. If a malfunction in the container-mounted sensor is detected, the operator informs maintenance personnel, which subsequently repair or replace the sensor.

III. OBJECTIVE RESPONSIBILITY QUANTIFICATION

In the context of the above fault scenario, the automated control system serves as a binary alert system for the presence of milk...
in the milk container. In this case, the ResQu model is reduced to relatively simple formulas [20,27].

Let $X$ denote the binary set of the action alternatives for the human, and $Y$ denote the binary classification set for the system. Then, the human causal responsibility is defined as

$$\text{Resp}(X) \equiv \frac{H(X|Y)}{H(X)} = \frac{H(X|Y) - H(X)}{H(X)}$$

where $H(X)$ is Shannon's entropy, which is a measure of uncertainty related to a discrete random variable $X$

$$H(X) = -\sum_{x \in X} p(x) \log p(x)$$

and $H(X|Y)$ is the conditional entropy, which is a measure of the remaining uncertainty about a variable $X$ when a variable $Y$ is known.

$$H(X|Y) = -\sum_{y \in Y} p(y) \sum_{x \in X} p(x|y) \log p(x|y)$$

The ratio $\text{Resp}(X)$ quantifies the expected exclusive share of the human in determining the action selection variable $X$, given the system’s classification $Y$. By definition, $\text{Resp}(X) \in [0,1]$. $\text{Resp}(X)=1$ if, and only if, the human action selection $X$ is independent from the system’s classification result $Y$. $\text{Resp}(Z)=0$ if, and only if, $Y$ completely determines $X$, in which case the human actions are exclusively determined by the system’s classifications.

To calculate the ResQu responsibility measure, for the selected fault scenario at the dairy, one must deduce the underlying distributions of $Y$ and $X$ and their mutual relation.

On average, the milk in a container suffices for 4 hours of production, and flushing and cleaning an empty container takes 1 hour. Thus, on average, in a 24 hour day there are $24/(4+1)=4.8$ milk cycles. In a working month, the factory works for 24 hours a day on 27 days. This amounts to an average of 129.6 milk cycles for each container.

On average, there are 4.8 true alerts a day (at the end of each milk cycle) for each container, indicating that the container is empty (True Positives). As presented above, a fault in one of the 30 milk container sensors occurs on average once a month (27 working days). Thus, for a single container, there is a daily average of $\frac{1}{36} \cdot \frac{1}{27} = 0.00123$ False Alerts, which falsely indicates that the container is empty. Thus, given an alert that a certain container is empty, there is a $4.8/(4.8+0.00123) \approx 0.99975$ probability that the alert is true. This is the Positive Predictive Value (PPV) of the automated system. Respectively, given an alert, there is only a $0.00025$ probability that it is false.

On average each container is refilled with milk, every 5-7 hours, in a process that requires the operator to manually connect pipes to the milk containers. Thus, the operator is somewhat able to assess independently whether a specific container contains milk by recalling when he or she last refilled that container. However, due to the large number of milk containers, this subjective assessment is not perfect. The operators estimated that they have a relatively good chance, of .9, to correctly and independently assess the true state of each milk container, whether it is empty or contains milk. Nevertheless, they may initiate cleaning of a container only when there is a relevant alert to do so. Table I summarizes the joint distribution of the true state of the container, and the operator’s perception of it, upon alert arrival.

| Operator’s perception upon alert | Empty | Not Empty | Marginal distribution of container |
|---------------------------------|-------|-----------|----------------------------------|
| True state of container         |       |           |                                  |
| Empty                           | 0.899775 | 0.099975  | 0.99975                          |
| Not Empty                       | 0.000025 | 0.000225  | 0.00025                          |

Thus (using Bayes’ theorem and Table I), with an alert, if the operator thinks that the container is empty, there is $0.899775/(0.899775+0.000025) \approx 0.99997$ probability that it is indeed empty. If the operator thinks that the container is not empty, there is still a very high probability of $0.099975/(0.099975+0.000225) \approx 0.97775$ that it is actually empty, due to the very high PPV of the system.

The operator’s action selection, given an alert, depends on the costs associated with wrong decisions (correct decisions and their related costs and benefits represent the nominal state of normal operation). When there is a false alert that a container is empty, and the operator complies with the alert and initiates automatic flushing, there is a direct average cost of 5,040 NIS, due to the price of the mean level of milk content in a milk container and the price of the detergents used. Besides this direct cost, there is also an indirect high cost, due to the damage to the operator’s reputation and competence in the eyes of the factory management and production line workers (the operator is not fined personally for such a mistake). When there is a true alert, but the operator wrongly thinks that it is false and goes to physically check the milk content in the container, there is an average cost of 750 NIS, which reflects the revenue loss, due to the 15 minutes delay in starting the next production cycle. Besides this direct cost, there is also an indirect cost, due to the physical effort involved in walking to the tanks, climbing the container and examining the milk level, and the cost of leaving the control room for 15 minutes, which may be problematic when the workload in the control room is high (e.g. in the morning, when many tank trailers with fresh milk arrive).

We now combine the above costs and probabilities to compute the optimal action selection that minimizes expected costs. Assume that when the alert arrives, the operator also thinks that the container is empty. Thus, the probability that the container is indeed empty is 0.99997, so if the operator wrongly chooses to physically go and inspect the milk content, there will be an associated average cost of 0.99997·750=749.98 NIS. However, there is still a very low chance of 0.00003 that the container is not empty, so there is an associated average cost of 0.00003·5040=0.14 NIS, to initiating the cleaning process. Thus, the optimal strategy, in this case, is to comply with the alert, by initiating the cleaning process. It is easy to show that this is also the optimal action when the operator sees an alert, but thinks that the container is not empty, upon alert arrival. Thus, the optimal strategy is to always comply with the alert, even if the operator suspects that it is false. This results from the very high PPV of the alert system, compared to the human, and the cost structure.
We now compute the objective ResQu responsibility measure, using (1). Under the above optimal strategy, the automated sensor classification (denoted by Y) completely determines the operator’s response (denoted by X). The operator should always initiate a cleaning process upon an alert, and do nothing when the signal is that “there is still milk”. In terms of entropies this actually means that $H(X|Y)=0$ since, given $Y$ (the type of systems indication), there is no uncertainty left regarding $X$ (the operator’s action selection). Thus, the ResQu objective measure for human responsibility equals zero. This is logical, since under the optimal strategy, the operator actually serves as a kind of a physical mean that only transforms system indications into prescribed actions, and hence has no true unique contribution to the action selection process.

IV. SUBJECTIVE RESPONSIBILITY ASSESSMENTS

We presented descriptions of three different fault scenarios, related to the failure discussed above, to different functions in the plant: a control room operator, a shift manager in the control room, a production line worker, the quality assurance manager of the dairy, and the chief financial officer of the diary. The participants filled out a questionnaire, providing their subjective judgments on the action selection and responsibility of the control room worker, in each of the scenarios. The action selection was rated on a 1-5 scale, where 1 is “didn’t act properly” and 5 is “acted properly” and the responsibility was rated on a 0-100% scale, where 0 is “not responsible at all for the losses” and 100% is “fully responsible for the losses”. We also asked the participants to explain their choices.

A. Scenario I – A Large financial loss due to incorrect cleaning of a container, while still full of milk

According to this scenario, during a busy morning shift, the control room was alerted that one container is out of milk and needs to be cleaned. The shift manager (who had filled that container with milk, about half an hour earlier) was absent from the control room, busy with another necessary task. The operator complied immediately with the alert and initiated a cleaning process. About 5 minutes later, a production line worker rushed to the control room and updated that this was a mistake and that the production must be stopped. About 2,000 liter of milk, in the container had to be discarded, which is equivalent to a loss of 10,000 NIS.

Fig. 1 presents the subjective scores, made by each of the functions in the dairy, in the first scenario. We can see that there is a large difference in the subjective assessment made by the control room operator, and those made by all the all the other functions in the plant.

The operator stated that the operator’s action, in the scenario, was mostly correct and that the operator’s responsibility for the losses is low. He explained that the operator acted in accordance with the alert, and that it is customary and logical to act in such a way, due to the high reliability of the alert system and the fact that many alerts arrive every day. The shift supervisor rated the operator’s action as wrong and held the operator fully responsible for the losses. He explained that the operator could have called back the shift supervisor for consulting, which might have prevented the damages.

Fig. 1. Subjective scores in the 1st Scenario.

The Chief Financial Officer (CFO) and Quality Assurance Manager (QAM) gave similar scores to those given by the shift supervisor. In their view, a full tank of milk had to be discarded because of the operator's mistake and because he did not consult with the shift manager. Thus, the operator acted wrongly and is fully responsible for the adverse outcomes. The production line worker had a similar assessment. From his point of view, in general, the control room operators are fully responsible for such mistakes, which stop production and cause more work for the production workers (e.g. extra cleaning activities, re-pasteurization, etc.).

To conclude, there was high diversity in the subjective ratings between the different functions, with a systematic tendency to subjectively assign high responsibility values to the operator, even though he complied with the alert (and thus objectively had zero causal responsibility).

B. Scenario II – A medium financial loss due to incorrect cleaning of a partially filled container

According to this scenario, toward the end of an afternoon shift, the control room was alerted that one container is out of milk, and needs to be cleaned. The operator remembered that this container was filled with milk some hours ago, so the alert seemed sensible. Due to being tired after a busy shift, the operator chose to comply with the alert and initiate a cleaning process. About 5 minutes later, a production line worker rushed to the control room and updated that this was a mistake and that the production must be stopped. About 400 liter of milk that were in the container had to be discarded - a loss of 2,000 NIS. This scenario is different from the previous one in two aspects. First, the incurred loss is smaller (2,000 NIS vs. 10,000 NIS). Second, there is a higher correlation between the timing of the alert and the possible state of the container, increasing the probability that the container did run out of milk. Fig. 2 presents the subjective scores, made by each of the functions in the dairy, in the second scenario.

The operator’s assessments were identical to those in the first scenario, justifying the action of the control room worker in the scenario and relating low responsibility for the loss. In his explanations he mentioned also the high correlation between the time passed since the container was filled and the timing of the alert, so the alert seemed logical. The shift supervisor the CFO, and the QAM justified the operator’s action, more than in the first scenario, and attributed only partial responsibility for the losses (compared to the full responsibility they gave in the first scenario).
This was since the operator action seemed more logical, considering the long time since the container was filled with milk. However, because there is still a considerable loss, they do find the operator responsible, though to a lesser extent than in the first scenario. The production line worker’s assessments were identical to those in the first scenario, attributing full responsibility to the operator. Again, there was a systematic tendency to relate higher responsibility, than the objective value.

C. Scenario III – A small financial loss due to the operator questioning the validity of the alert

According to this scenario, during a busy morning shift, while the control room is temporarily manned only by the operator, the control room was alerted that one container is out of milk and needs to be cleaned. However, it seemed to the operator that he had filled this container only two hours ago, and thus he suspected that this is a false alert. He chose to go to the storage area and physically check if there is still milk in the container. In the inspection, he discovered that the alert was correct and there was no milk, so the container needs to be cleaned. He went back to the control room and initiated cleaning. As a result of the inspection, a 15 minutes delay to the daily production process was created, which is equivalent to loss of 750 NIS. Fig. 3 presents the subjective scores, made by each of the functions in the dairy, in the third scenario.

In this scenario, the operator justified again the action of the control room worker. He explained that if the operator really suspected a false alert, he should conduct another examination, due to the high costs of falsely initiating cleaning. Contrary to previous scenarios, the quality assurance manager supported the operator’s assessments, stating that the control room worker acted correctly and has low responsibility.

She explained she always prefers to check if there is any doubt related to the production process, to avoid unnecessary major errors, even if this involves “minor” costs. Most other evaluators also believed that the operator acted correctly, since if it was a false alert, the remaining milk would be discarded, and since the price for doing so was rather low. At the same time, the shift supervisor, the CFO, and the production worker, still considered the operator responsible for the unnecessary financial loss, due to the unnecessary delay he created.

V. DISCUSSION

In the selected fault scenario, due to the high abilities of the automated alert system (high PPV), compared to those of the operator, and the structure of the payoff matrix, a rational operator, who minimizes expected costs over time, should always act according to the indications from the automated system. In this case, the automation unequivocally dictates the operator’s actions. Thus, the operator has no unique marginal contribution, and has no causal responsibility for the outcomes.

The results showed differences in the perception of responsibility amongst various functions. First, even though in the firsts two scenarios the operators acted in accordance with the optimal theoretical behavior, by fully complying with the alerts, and thus had zero responsibility, they seemed much more responsible in the eyes of senior management. Second, in all three scenarios there was a systematic tendency to subjectively attribute more responsibility to another person than to oneself, in a manner that resembled aspects of the “fundamental attribution error” in social psychology. This tendency was also noted in our previous study [27].

The above findings have important implications, regarding the responsibility attributed to control room operators, and in general, to human interaction with intelligent systems.

When an operator’s actions are entirely dictated by a strict procedure that is based only on automatic indications that are presented in the control room, the operator actually acts as a kind of a physical mean that only transforms system indications into prescribed actions. In this case, the operator has no unique contribution, and the objective human causal responsibility is zero. However, our results showed systematic tendency of outside observers, such as managers, to subjectively attribute much higher responsibility. This, in turn, may lead to unjustifiably holding operators responsible for adverse outcomes in situations in which they rightly trusted the automated system, and acted according to its indications.

More generally, when humans interact with advanced intelligent systems, in which they should contribute very little to determining the actions, there could be a discrepancy between their role responsibility (i.e. the duties which they are held accountable for) and their causal responsibility (i.e., their actual contribution to outcomes). The human may be considered fully legally responsible for adverse outcomes, even when not having sufficient control to prevent them or when contributing very little to create these outcomes.

System designers frequently keep humans in the loop to supervise the automation and handle unexpected events. Our results demonstrate that simply putting a human into the loop does not assure that the human will have a meaningful role and
unique contribution to the process. Organizations should consider the true added value of the human to system processes, beyond the simple role of approving system decisions.

Falsely claiming that the human is responsible for adverse outcomes, even when the person actually contributed very little to generate them, may expose the human to unjustified legal liability and to the psychological burden of self-blaming.

The ResQu model can be a useful tool for objectively analyzing causal responsibility between the humans and intelligent systems. As such, it can aid system design and guide policy and legal decisions.

D. Limitations and future work

The current analysis is clearly an initial step in the complex task of applying the ResQu model to quantify real-life human responsibility in intelligent systems. As a very first application it was limited to a simple automation and a single type of failure scenario. Future work should address more complex automations and types of interaction. Also, we obviously did not conduct a systematic quantitative study, and the respondents’ statements should be considered as anecdotal. Still in many settings one cannot conduct systematic surveys, because there are simply too few people who fulfill specific roles in the organization. Hence research will necessarily be more qualitative in nature, similar to the study we present here. Still, the study does serve as a proof-of-concept and a systematic demonstration of the evaluation of causal responsibility in human-automation interactions.

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