Quantifying the Effectiveness of an Alarm Management System through Human Factors Studies

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Highlights

- Alarm systems are critical to ensuring safety in chemical plants
- Real benefit of alarm systems can only be identified through human factors experiments that evaluate how operators utilize the decision support systems
- In this paper, we experimentally quantify the benefits of early warning
- Our results indicate that Early Warning is helpful in reaching a diagnosis more quickly
- However it does not improve the accuracy of correctly diagnosing the root cause

Abstract

Alarm systems in chemical plants alert process operators to deviations in process variables beyond predetermined limits. Despite more than 30 years of research in developing various methods and tools for better alarm management, the human aspect has received relatively less attention. The real benefit of such systems can only be identified through human factors experiments that evaluate how the operators interact with these decision support systems. In this paper, we report on a study that quantifies the benefits of a decision support scheme called Early Warning, which predicts the time of occurrence of critical alarms before they are actually triggered. Results indicate that Early Warning is helpful in reaching a diagnosis more quickly; however it does not improve the accuracy of correctly diagnosing the root cause. Implications of these findings for human factors in process control and monitoring are discussed.

Keywords: Alarm Management, Process Monitoring, Prediction, Process Operators

1. Introduction

Modern chemical plants consist of a large number of integrated and interlinked process units. To optimize production, process operators and engineers depend on automation systems to extract information (e.g. through thousands of sensors) and to assist them in the management of operations (e.g. through built-in controllers). Abnormal situations result in process variables moving away from their desired ranges and potentially lead to undesired outcomes. Automation systems will alert the operators of such occurrences through alarms. As process units are highly interlinked, deviations due to an abnormal situation could propagate through various process units and numerous variables. This may lead to many alarms occurring at the same time (Liu et al., 2003; 2004). The operators have to make sense of the barrage of alarms, quickly and accurately identify the root cause of the abnormal situation, and take corrective actions to rectify the root cause and bring the process back under control.

An abnormal situation can sometimes have serious repercussions, including considerable economic impact on plant profitability due to unacceptable product quality, plant downtime, or even the loss of life. Thus, there is a need to develop a dependable system that enables the operators to quickly and correctly diagnose the root cause of the abnormal situation and design and implement suitable corrective action. With early intervention, losses resulting from abnormal situations can be minimized by avoiding the worst case scenario of a catastrophic loss (Burns, 2006). A number of decision support systems have been developed to enable the operators to diagnose the root cause of the abnormal situation.

In order to ensure that the potential offered by such tools are in fact translated to operational benefits, one needs to consider the complementary aspect of human factors. Human factors is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system in order to optimize overall system performance (International Ergonomics Association, 2014). Process control typically entails working in a complex, interactive system involving hardware, software, and humans. The human aspect is widely considered to be very important but paradoxically has received significantly less attention, especially in the process systems engineering (PSE) community. We seek to address this issue in this paper. Specifically, we seek to understand how operators would interact with decision support systems for alarm management and quantify the real benefits through human factors experiments. Section 2 presents a review of alarm management systems and the pivotal role of operators in chemical plants. This is followed in Section 3 by the human factors experimental methodology adopted in this research. Results of the human factors study are presented in Section 4. Section 5 concludes with suggestions on future research work.

2. Literature Review

Complexity has been increasing as a result of increased sophistication in chemical processes to allow for larger amounts of material and energy integration, environmental regulation, and the greater need for optimization and efficiency (Chu et al., 1994; Wall, 2009). With this increased pressure to 'do more with less' (Jamieson and Vicente, 2001), effective process control systems are all the more critical to ensure safe and smooth operations. This is often achieved by the application of modern digital technology and increasing automation. However, an unintended consequence of increased sophistication is the greater challenges faced by operators, especially when managing abnormal situations (Chu et al., 1994).

During abnormal situations, there are real risks of operators not receiving important alarm information to take corrective actions in time, which could have potentially serious repercussions. One such incident occurred at Texaco's Oil Refinery, Milford Haven, United Kingdom (UK) and led to the explosion that took place on 24 July 1994, in which 26 people sustained minor injuries. Financial losses resulting from this explosion included 48 million pounds in reparation and substantial losses in production (Bransby and Jenkinson, 1998). It has been reported that in the 10.7 minutes prior to the explosion, the two operators on duty were flooded by 275 alarms. Apart from this alarm barrage, the UK Health and Safety Executive (HSE) cited poorly designed control display and inefficient alarm prioritization as two of the main contributing factors for this incident. The UK HSE has estimated that a typical oil refinery can avoid three to ten million pounds losses per year through proficient alarm management and better operator support system (Bransby and Jenkinson, 1998).

A number of guidelines have been developed to improve alarm management systems, e.g. by International Society of Automation (2009) and the ASM consortium (2009). Various algorithms and techniques have been developed to reduce the total number of alarms that will be activated (Liu et al., 2003; 2004). Foong et al. (2009) developed a fuzzy-logic based alarm prioritization (ALAP) system to prioritize alarms during alarm floods so as to reduce the burden of operators from meaningless or false alarms. A novel alarm reduction method that involves data-mining to spot the statistical similarities among operations and alarms has been reported by Higuchi et al. (2009). Brooks et al. (2004) deemed the root cause of poor performance of alarm systems to be the single-variable and empirical methods of setting alarm limits. They examined multi-variable alarms and proposed a geometric process control method. These demonstrated a substantial reduction in false alarms in field trials conducted in chemical plants in the UK. Cheng et al. (2012) identified similarities between alarm flooding situations by employing a modified Smith-Waterman algorithm to analyze the alarm flood pattern and cluster similar ones.

Even with automation and improved alarm management systems, human operators still remain irreplaceable in the control of chemical plants, especially during abnormal situations (Parasuraman and Wickens, 2008). The human operator has different roles and responsibilities in the chemical plant that is largely dependent on the plant states (Brown and O'Donnell, 1997; Emigholz, 1996). Under normal operating conditions, the operator is able to assume a relatively passive role in supervising the unit operation with a focus on maximizing efficiency of the process unit by making minor adjustments to the process variables. However, when an abnormality occurs, the operator would need to proactively manage the situation by taking corrective actions to manipulate the process unit back to the normal operating conditions. Automation is less error-prone and can be relied on to produce repeatable actions, but generally fails to address abnormal situations which are likely to be unforeseeable. Nachtwei (2011) noted that in contrast with automated systems, humans have the ability to be flexible and to produce creative solutions in response to unanticipated situations. This ability of the operators to effectively devise solutions for abnormal situations is contingent on their situation awareness.

Situation awareness and human factors have been widely studied in a variety of domains including process control (Endsley, 1988; Endsley, 1995; Stanton et al., 2001), plant design (Kariuki et al., 2007; Widiputri et al., 2009; Cullen, 2007), and process risk analysis (Kariuki and Lowe, 2006). The key steps in situation awareness are perception of the environment, comprehension of the current situation, and prediction of future status. To support situation awareness, the human factors community has developed experimental techniques for user interface design and evaluation (Kontogiannis and Embrey, 1997; Spenkelink, 1990; Tharanathan et al., 2012; Nishitani et al., 2000). In this paper, we adopt such experimental techniques to study the human factors that affect alarm management. Specifically, we seek to understand and quantify the benefits of decision support tools and evaluate their effectiveness. Although a variety of alarm management tools and techniques have been proposed in literature, their effectiveness has not been systematically studied. The interaction between operators and a decision support tool can only be closely examined through experiments involving human participation as described next.

3. Experimental Methods to Study Human Factors

The cognitive tasks performed by an operator during abnormal situations generally follow three steps: orientation, diagnosis and execution (Chu et al., 1994). When faced with an abnormal situation, the operator would first need to orient himself and focus on understanding the particular situation through the search for relevant information. The next step involves diagnosing and evaluating the situation by interpreting the information and relating the data to possible causes of abnormality. This may result in one or many postulated root causes. The execution step refers to the actions taken to verify the malfunction postulations, as well as the corrective actions taken in the attempt to bring the process back to normal. An alarm management system could make the operators more effective in the orientation and diagnosis tasks. We have developed an experimental scheme to evaluate if a decision support tool is effective in improving operators' performance in these tasks. Although the general strategy is broadly applicable to any process monitoring and diagnosis decision support system, we have applied it in the context of early alarm warnings.

Early Warning predicts the time of occurrence of critical alarms before they are actually triggered (Xu et al., 2012). Predictive aids that help users anticipate future system states have been widely used in various domains, e.g. the cockpit display in modern aircrafts that predicts the trajectories of other aircrafts in the proximity and alerts the pilots of any potential conflicts, or hurricane forecast that predicts where an oncoming hurricane will and will not strike. However, predictive aid is still not practiced in the area of alarm management in chemical plants. Early Warning provides control room operators with anticipatory information on incipient alarms that could happen within a certain time window (e.g. the next 60 seconds). This allows the operators to be more proactive as they are alerted early on potential problems so that they can anticipate, evaluate, and start taking corrective actions even before alarm thresholds are breached.

Our current work focuses on quantifying the benefits of Early Warning in supporting operators, specifically the extent of time advantage gained by operators and the resulting improvement in diagnosis accuracy. We have designed an experimental scheme to address this primary research question. The study compares the performance of participants in the supported case with Early Warning to the unguided case where the operator has no decision support tools and relies solely on the alarm system to detect and diagnose abnormalities. Performance is measured based on their diagnosis of the root cause of a given abnormal situation scenario. More specifically, there are two performance measures: diagnosis lag and diagnosis accuracy. Since Early Warning provides the same type of alarm information to the participants, only earlier, it is not expected to change their cognitive processes. Any change in participants' performance can thus be attributed to Early Warning.

3.1 Case Study

The case study considers the simulation of a depropanizer unit motivated by a real refinery (Xu et al., 2012), a schematic of which is shown in Figure 1. The depropanizer unit serves to separate the feed mixture, consisting primarily of C3 and C4 hydrocarbons, into two product streams. The lighter product from the top of the unit consists primarily of C3s while the heavier product from the bottom of the unit consists of C4s and heavier hydrocarbons. There are three main sections, i.e. distillation tower, reboiler, and condenser. The depropanizer unit has 23 measured process variables, out of which eight are important process variables that have alarms configured (Table 1). Information on past and current values of process variables and triggered alarms is conveyed to the participants through displays.

3.2 Diagnosis Tasks

In this study, the main activity of participants from which performance measures are derived is the diagnosis task. Participants are asked to monitor the depropanizer unit and different scenarios are simulated. Each scenario involves a particular fault resulting in a sequence of alarms. The participants' task is to diagnose the root cause of the fault.

A total of six fault scenarios are used in the study. They are: (1) Reflux pump degradation, (2) Loss of cooling water at condenser, (3) Loss of hot oil at reboiler, (4) Loss of feed, (5) Reboiler fouling, and (6) Condenser fouling. Each fault will cause different alarms to be triggered at different times. The sequence of alarms that are triggered in each fault scenario is shown in Table 2. For example, in the first scenario, the reflux pump (P11A in Figure 1) degrades. Consequently, the reflux flow into the distillation tower decreases and temperature of the top tray, *TI17*, increases due to less cooling. Hence, the high-limit alarm TI17 HI is eventually triggered. Also, since less reflux is being pumped back from the reflux drum, the liquid level in the reflux drum, *LC12*, starts to increase and LC12 HI alarm is triggered. Subsequently, temperatures in the lower trays of the distillation tower are also affected by the reduced cooling and the high-limit alarms of *TI16*, *TI14*, *TC11*, and *TI13* are triggered. Due to less condensation, liquid level in the bottom hold-up, *LC11*, decreases and LC11 LO alarm is triggered. Vapor continues to build up in the distillation tower and eventually the column pressure *PC11* high-limit alarm is triggered.

In each scenario, participants will see a sequence of alarms in real-time. The participant is free to submit his diagnosis at any point during the scenario, even before the scenario ends. The duration of each scenario is limited and participants are clearly informed when the scenario has come to an end and no additional process measurements or alarms will be provided. Based on the alarms and the information on the 23 measured variables available through the Schematic Display (including current value and trend, see below), they have to diagnose the root cause of the fault and submit their diagnosis by selecting from a dropdown list, which includes all the six faults as well as the null choice "None of the above" (Table 3). From Table 2, it can be seen that scenarios 1 and 4 each have a unique alarm sequence. However, scenarios 3 and 5 have the same alarm sequence and so do scenarios 2 and 6. The former pair can still be differentiated since the hot oil flow (*FI16* in Figure 1) will be zero in scenario 3 (loss of hot oil). On the other hand, cooling water flow is not a measured variable in this process, so scenario 2 (loss of cooling water) and scenario 6 (condenser fouling) are not differentiable. Either of the two answers is therefore accepted as correct in these two scenarios.

Participants' performance is scored in each scenario using two performance measures: diagnosis accuracy and diagnosis lag. Participants may obtain a diagnosis accuracy score of 0, 0.5 or 1, depending on their choice for a scenario. A full score of

1 is given for correct identification of the root cause. Among the six scenarios, some have similar symptoms as they originate from the same area. The fault in scenario 1 (reflux pump degradation), scenario 2 (loss of cooling water), and scenario 6 (condenser fouling) all originate in the condenser area, while the fault in scenario 3 (loss of hot oil) and scenario 5 (reboiler fouling) originate in the reboiler area. A partial score of 0.5 is given if a participant selects a wrong diagnosis but from the same area. All other diagnosis choices are given a 0 score. This diagnosis accuracy scoring scheme is summarized in Table 4. Diagnosis lag is the time taken to formulate the diagnosis, which is taken to be the interval between the start of the scenario and the submission of the diagnosis.

3.3 Displays

Information about the status of the process is provided in real-time to the participants via two displays, namely the Schematic Display (Figure 2) and the Alarms Display (Figure 3). The Schematic Display provides an overview of the different components within the depropanizer unit. The current (real-time) value of each of the 23 variables is shown adjacent to the variable name. Historical trend of each variable can also be viewed by clicking on the small grey box near the variable, which will bring out the Trend Display in a small inset at the bottom left of the Schematic Display, showing the variable trend line based on the last 10 samples (20 seconds) as well as the high/low alarm limits. For example, Figure 2 shows the Trend Display of variable *TI14*. When a variable with a configured alarm goes outside its normal operating range, the trend will cross the alarm limit line and the color of the variable value in the Schematic Display will turn from green to red. In addition, an alarm will sound and the details of the variable will be shown in the Alarms Display (bottom of Figure 3).

The alarm information is traditionally presented in a list form like the Alarm Summary table, shown in the bottom part of Figure 3. In our Alarms Display, we additionally show alarm information graphically through the Alarm Pane (see top part of Figure 3). The Historical Pane within the Alarm Pane shows temporal trends of alarms that have occurred in the recent past, e.g. last one minute. Alarms are grouped into four quadrants, based on their location in the Schematic Display. Each alarm is depicted as a triangle that either points upwards to represent a high-limit alarm or downwards to represent a low-limit alarm. For example, Figure 3 shows four alarms that have occurred in the last one minute, i.e. PC11 HI (20 seconds ago), TI16 HI (12 seconds ago), TI13 HI (nine seconds ago), and TI17 HI (one second ago).

The Alarm display is augmented in the Early Warning decision support case. In this case, there is an additional pane called the Prediction Pane, located right of the Historical Pane. This pane shows early warnings of alarms that are predicted to happen within the prediction window, e.g. in the next 15 seconds (Figure 4). Early warnings are also included in the Alarm Summary table. For example, Figure 4 shows that TI13 HI is predicted to occur in the next one second and TI17 HI within the next 12 seconds. When TI17 HI actually occurs, this early warning is removed from the alarm list and replaced by the actual alarm information.

Both the Schematic Display and the Alarms Display were developed in MATLAB (Mathworks, 2013). Each fault scenario was simulated beforehand in an operator training simulator (Helander, 2011) to generate the process variable values. This data is then read into MATLAB at regular intervals (one sample every two seconds) and presented to the participants through the displays. Due to the large sizes of the displays, two monitors are used. The Schematic Display is shown in the left monitor and the Alarms Display in the right monitor. The dropdown list of diagnosis options is located at the top right part of the Schematic Display (Figure 2). Participants can select their diagnosis from this list and submit anytime during the scenario.

3.4 Key Human Factors Principles

The study was conducted in a controlled laboratory environment that simulated the real-life setting in a chemical plant control room. The simulated experiments may differ from the environment in the plant due to simplifications in the nature and manner that information is conveyed to the participants. However, the laboratory setting enabled us to ensure that there is no impact on actual operations in a real plant, eliminating any concomitant risks to process operations and safety. Some key features of the experimental scheme are discussed below.

Deceptive Experimental Technique

Withholding information regarding the true objective of the study from participants is a common experimental technique in psychology studies (Hertwig and Ortmann, 2001). There are several justifications for this, including the concern that participants' behavior could be affected by the knowledge of the study objective and result in participants forming biased opinions and attitudes towards the study objective, which would likely be reflected in the results they produce. It might also lead to participants responding strategically during the experiment in an attempt to assist or ruin the experimenters' hypotheses (Walster et al., 1967).

In this research, a general term, "Process Analysis Study", was adopted as the study title. Prior to the studies, participants were not explicitly informed that the underlying objective was to evaluate the Early Warning decision support system. They were only told that their role was to monitor the system and provide an analysis to the engineer on duty. This prevented any instances of participants deliberately altering their behavior in accordance to the type of display they were shown. In this way, we ensured that the experimental results are reliable and not biased. However, it is also important to note that this might result in participants second-guessing the actual purpose of the experiment. This issue could be overcome by providing participants with clear instructions, as elaborated in the next section.

Role Playing

Participants could form diverse interpretations of the experimental situation and react differently even when given the exact same experimental setup (Hertwig and Ortmann, 2001). This emphasizes the importance of providing precise experimental specifications in an attempt to lessen participants' uncertainty. A good way to do so is to clearly define the role that participants are to assume during the experiment. Clearly informing the participants of the role they play prevents them from forming their own expectations of what the experimenters are testing for. Task instructions that are explicitly provided serve to focus the participant's attention on the experimental expectations, thus removing any ambiguity of the experimental situation. This improves the experimenters' control over participants' possible interpretations of the experiment and enhances reproducibility of the study results.

In the context of this research, participants were assigned the role of chemical plant operators, where they were asked to monitor the process plant and diagnose abnormal situations. This instruction was clearly provided to all participants at the start of the studies. This reduced the necessity of participants having to infer the meaning of the experiment.

Providing Learning Opportunity

By exposing participants to more than one diagnosis task, the experimental setup provides them with learning opportunities as the participants can gain experience through increased familiarity with the experimental setup. Hertwig and Ortmann (2001) identified two types of learning that occurs during human experiments. The first type is related to adaptation to the experimental environment, where participants should be given the chance to familiarize themselves with the experimental procedures and clear any doubts regarding the laboratory set-up and task expectations. The second learning involves gaining a better understanding of the task situations and recognizing any possible strategic aspects in handling the situation. A high variability in study results is likely to be observed if data is obtained from a task that is performed only once, as there is less consistency in performance level. The more often the participants are given a similar task, the more consistent are their resulting behavior and thus the results obtained.

In the studies that were conducted, familiarization activities were present in the form of detailed instructions on handouts and video walkthroughs. The study had a total of six diagnosis tasks. The first task (for both the supported case and the unguided case) was not included in the result analysis. This is to account for participants who might still be unfamiliar with the experimental set-up, which could lead to the results in these initial tasks not being a true reflection of the required cognitive processes.

3.5 Experimental Design

The whole study is designed around the diagnosis task. There is one independent variable and two dependent variables (performance measures) in the study. The independent variable is the type of case: supported (with Early Warning) or unguided (without Early Warning). The dependent variables are diagnosis lag and diagnosis accuracy as described above.

In this study, we adopted a within-subjects, repeated-measures experimental design. Each participant participated in both the supported case and the unguided case. There are two key advantages to this design: (1) more observations, and (2) reduction in error variance associated with individual differences (Hall, 1998). For the same number of participants, a within-subjects design will result in twice as many observations as a between-subjects design. For example, if we have 20 participants, a between-subjects design will split them into equal size groups: one group of ten will do the supported case and the other group of ten will do the unguided case, resulting in 10 observations each for the supported case and the unguided case. Using the within-subjects design, all 20 participants will do both the supported case and the unguided case resulting in 20 observations for each. As the number of observations increases, the probability of beta error (i.e., not finding an effect when one exists) decreases. The second advantage of a within-subjects design is that variance due to individual difference factors are minimized since the participants are the same for both the supported case and the unguided case. Factors such as individual background knowledge, intelligence, and deductive capability will be exactly the same for the two cases because they are the exact same group of people.

On the other hand, a fundamental disadvantage of the within-subjects design is the "carryover effect", which means participation in the earlier case may affect performance in the later one. Two possible carryover effects are practice and fatigue. While a participant is doing the first case, e.g. an unguided case, he is also becoming more familiar with the system and the diagnosis task, so that by the time he is about to do the supported case, he has more understanding of the process. This practice effect may cause a bias where performance in later tasks tends to be better due to practice and increased familiarity. On the other hand, the fatigue effect is where the participant gets more tired or mentally fatigued in the later part of the experiment, thus negatively affecting his performance in the later tasks.

To minimize the practice effect, we provided participants with video walkthroughs and an opportunity to familiarize with the system in their first task. The first task in each case is a dummy task, which is not taken into account in the result analysis. It serves as an opportunity for the participant to familiarize themselves with the displays and the diagnosis task. The participants are not informed of this as they might not take the task seriously if they know that it would not be counted. Fatigue effect is minimized by designing the study to take no more than 30 minutes in total. The overall carryover effect is also minimized by randomizing the order of cases (supported and unguided) and scenarios for the participants so that there is no bias resulting from order position for any particular case or scenario.

3.6 Experimental Procedure

Based on the above principles, the following experimental procedure was devised. There are two main cases in the study: supported and unguided. Each case consists of three diagnosis tasks; in total each participant performs six diagnosis tasks, corresponding to the six fault scenarios described in Section 3.2. Scenario 2 is selected to be the first task (dummy) for the unguided case and scenario 5 for the supported case. The remaining four scenarios can be grouped based on the number of alarms; scenarios 3 and 4 have fewer alarms and are of low-intensity than scenarios 1 and 6 (Table 2) which are of high-intensity. Thus, for a fair comparison between the two cases, each case consisted of one task from the low-intensity group (scenarios 3 or 4) and one task from the high-intensity group (scenarios 1 or 6) in addition to the dummy task. The scenarios from the two groups are assigned to the two cases randomly in equal proportion. Participant A might get Scenarios 3 and 1 in the supported case and 4 and 6 in the unguided case, while Participant B gets scenarios 3 and 6 in the supported case and 4 and 1 in the unguided case. But in total, the number of scenario 1 tasks in the supported case and the unguided case from the whole study will be comparable.

A flow diagram illustrating the study procedure is shown in Figure 5. At the start of the study, participants are briefed using three handouts:

1) Overview handout, describing their role as plant operator who is monitoring the process unit and required to provide both correct and timely fault diagnosis
2) Technical handout, describing the depropanizer unit
3) Display handout, describing the Schematic Display and the Alarms Display and how the information can be accessed and interpreted

They then proceed to do the tasks in the first case, which has been randomly assigned to be either supported or unguided. Before starting the tasks in each case, participants are shown a training video to help them familiarize with the system and ensure that they are clear of what they are expected to do during the tasks. The video is a walkthrough guide of an actual fault scenario with a narrator saying aloud her/his thinking process as (s)he sees the alarms until the time (s)he concludes her/his diagnosis and submits it. The participants then proceed to the first diagnosis task in the case. At the end of the diagnosis task, a task-survey containing two questions (shown in Table 5) is conducted to get the participants' subjective assessment about the task. Then the participants proceed to the second task. Once the participants have completed all the three tasks in the first case, they move on to the second case. Similarly, the second case also starts with a video walkthrough of the new display type followed by three sets of diagnosis tasks and survey questions. After all the three tasks in the second case are completed, a final survey containing six questions (shown in Table 6) is conducted to get the participants' overall subjective assessment of the displays.

The whole study procedure is implemented and managed using the Morae software from TechSmith Corporation (Morae, 2012). Instructions are shown on-screen and participants move forward from one part to the next as prompted and guided by Morae. The following data from the study is recorded using Morae Recorder: participants' mouse movements, mouse clicks, diagnosis choice, diagnosis time, and survey answers. The recorded data can then be evaluated using Morae Manager for result analysis.

4. Results

The setup for the study is portrayed in Figure 6. A total of 61 chemical engineering students comprising 44 males and 17 females participated in the study. Fifty six were 3rd year (Junior) or 4th year (Senior) undergraduate students and five were postgraduate students. Thus, even though they had little or no prior industrial experience, they can be reasonably assumed to have the background knowledge of fundamental chemical engineering principles and specifically distillation units. This is confirmed by their task survey response (Table 7). Only 7.5% feel that they cannot follow the development of the process during the task and less than 20% are not confident of their analysis. The majority of the participants can be considered to have sufficient background knowledge and therefore suitable for the study.

The human factors study aims to evaluate the effectiveness of Early Warning in a simulated environment, measured in terms of diagnosis lag and diagnosis accuracy. The study therefore focuses on two hypotheses in quantifying the advantage of offering decision support to operators, specifically through Early Warning, in the supported case over the unguided case.

H1: Participants require shorter diagnosis lag in the supported case with Early Warning as compared to the unguided case.

H2: Participants have better diagnosis accuracy in the supported case with Early Warning as compared to the unguided case.

In addition, a subjective assessment through survey was also conducted. Each of these is described next.

4.1 Diagnosis lag

Diagnosis lag is measured as the time from the start of the scenario until the participants submit their diagnosis. Each of the 61 participants did two actual tasks in the supported case and two in the unguided case, resulting in a total of 122 supported tasks and 122 unguided tasks. In this work, any data point that is more than 1.5 inter-quartile ranges below the first quartile or above the third quartile is considered as an outlier and excluded from the analysis (Moore and McCabe, 1999). Four supported samples and two unguided samples with significantly longer lag than the rest were therefore excluded. The detailed results are shown in Table 8. The mean diagnosis lag is 124 seconds in the supported case and 144 seconds in the unguided case. The median is 101 seconds in the supported case and 126 seconds in the unguided case. Thus, both mean and median statistics suggest that the supported case results in shorter diagnosis lag than the unguided case by about 20 seconds. The non-parametric Mann-Whitney U test (Mann and Whitney, 1947) is used to compare the two sets of data and the difference is found to be statistically significant at the 95% confidence level (p-value = 0.033 < α = 0.050). Thus, the hypothesis H1 that participants require shorter diagnosis lag in the supported case with Early Warning is validated.

This improvement in lag is expected as Early Warning provides participants with a time advantage, as illustrated in a simple single alarm case in Figure 7. In the unguided case (Figure 7a), participants are first alerted of the alarm at time $T_A{}^U$. After being alerted of the alarm, they take ($T_E{}^U - T_A{}^U$) seconds to diagnose the fault before they submit their diagnosis, which signals the end of the scenario at time $T_E{}^U$. In the supported case with Early Warning (Figure 7b), they are notified in advance about the potential alarm at time $T_{EW}{}^S$, before the alarm is activated at time $T_A{}^S$ (= $T_A{}^U$). Thus, they gain a time advantage of $t_{EW}{}^S = (T_A{}^S - T_{EW}{}^S)$ seconds. This time advantage means that they could start their diagnosis process earlier by $t_{EW}{}^S$ seconds and potentially complete their diagnosis earlier too at $T_E{}^S < T_E{}^U$.

From the mouse click data, we can analyze the participants' actions to check if and how the time advantage is actually utilized. In particular, the time of the clicks on the alarm variable trend display relative to the time when the alarm is shown on the Alarms Display window could provide an indication regarding participants' usage of the information. A mouse click to open the corresponding alarm variable trend display within 30 seconds after the alarm is shown is considered to be a consequence of the participant seeing the alarm information. With Early Warning, the participants are alerted to potential alarms and they are able to click on the relevant trend displays for further information before actual activation of the alarms. For example, in scenario 1 (reflux pump degradation), the first alarm TI17 HI occurred at time $T_A{}^U = T_A{}^S = 24$ seconds. In the unguided case, after this alarm was activated, 17 out of 30 participants proceeded to open the Trend Display of *TI17*, on average 9 seconds later. Other variables also entered alarm status and based on this information, the participants diagnosed the root cause and submitted their diagnosis on average at $T_E{}^U = 174$ seconds. In the supported case, a similar number, 17 out of 31 participants, opened the Trend Display of *TI17*. However, in this case there was Early Warning for TI17 HI at time $T_{EW}{}^S = 10$ seconds, resulting in a time advantage of $t_{EW}{}^S = 14$ seconds. Eight out of the 17 who opened the Trend Display of *TI17* did so on average 5 seconds before the alarm is activated at $T_A{}^S = 24$ seconds. Early warnings for the subsequent alarms were also given and the participants eventually submitted their diagnosis on average at $T_E{}^S = 153$ seconds. Hence, the use of Early Warning in Scenario 1 resulted in a time benefit of $T_E{}^S - T_E{}^U = 21$ seconds. Similar behaviour was observed in the other scenarios as well.

The alarm time, Early Warning time, and time advantage of each alarm in the four actual task scenarios are shown in Table 9. For these four tasks, there were a total of 19 alarm predictions and the average early warning notification time ($t_{EW}{}^S$) was approximately 28 seconds. This was the average time advantage that Early Warning provided to the participants. Among the participants who utilized the time advantage across all four actual tasks, it was found that on average, they opened the corresponding trend display 14 seconds before the activation of the alarm. The time advantage that was utilized averaged to 46%, with the maximum utilization being 82%. This shows that participants are indeed utilizing the time advantage provided to them. With Early Warning, the participants received information about the state of the plant earlier and they utilized the information earlier as well, thus resulting in the ability to formulate a diagnosis with a shorter lag.

4.2 Diagnosis Accuracy

The second performance measure is diagnosis accuracy, where participants' diagnosis in each actual task is given a score of 0, 0.5, or 1. In this case, there are no outliers as all data points are bounded between 0 and 1. The non-parametric Mann-Whitney U test is used to compare the two sets of data in each scenario. The results for each scenario are shown in Figure 8, where each error bar shows the 95% confidence interval. In all four scenarios, the difference between the supported case and the unguided case is not statistically significant at the 95% confidence level. Scenario 1 has the largest difference, where the mean score for the supported case (0.597) is lower than the unguided case (0.733), with p-value = 0.071. In the other three scenarios, the mean scores from the two cases are comparable with no statistically significant difference (p-value = 0.425, 0.548, and 0.286 for scenarios 3, 4, and 6, respectively). The overall results combining all four scenarios are shown in Table 10. The mean score for the supported case (0.648) is slightly lower than the unguided case (0.701), but this difference is not statistically significant at the 95% confidence level (p-value = 0.174 > α = 0.050). Thus, the hypothesis H2 that participants have better diagnosis accuracy in the supported case with Early Warning is not validated. This could be because the information provided to the participants is actually the same; Early Warning only shows this information earlier. The thought processes after receiving the information would be the same and thus the same diagnosis would be reached, only earlier. Hence, Early Warning does not seem to improve diagnosis accuracy.

4.3 Differences between High and Low Scorers

It is also interesting to analyze if there are any differences between participants who did well in the study and those who did not. For this, the participants were ranked according to their total score from the four actual tasks. We found that they could be divided into three groups of comparable size: 21 participants had scores between 4.0 and 3.5, 20 participants between 3.0 and 2.5, and 20 participants between 2.0 and 0.0. We call the first group as "High Scorers" and the last group as "Low Scorers" and compare these two groups to identify any patterns in behavior that could distinguish them. The supported case and the unguided case are separated to see how the two groups perform in each case. The difference in behavior was analyzed based on diagnosis lag and mouse click patterns, as shown in Table 11.

High Scorers generally perform better than Low Scorers in both diagnosis accuracy and lag. Looking into each group, the earlier finding that Early Warning leads to shorter diagnosis lag holds true for both High Scorers (116 s vs. 131 s) and Low Scorers (143 s vs. 155 s). It can be seen that Early Warning reduces the average number of clicks for both groups (4.48 to 3.81 for High Scorers and 5.75 to 3.80 for Low Scorers), but increases the percentage of clicks on alarm and related variables, especially for Low Scorers (clicks on alarm variables increased from 56% to 70%, while clicks on related variables increased from 78% to 89%). An alarm variable is a variable that has breached its alarm limit and trigger alarm. Here, 'related' variables refers to those variables that contain important information specific to the abnormal situation. This shows that Early Warning helps to focus the participants' attention to the relevant variables. However, this does not necessarily translate to higher diagnosis accuracy. High Scorers are able to maintain their diagnosis accuracy at a high level (0.94) regardless of early warning of alarms. Providing them with Early Warning leads to faster diagnosis with no loss of accuracy. In contrast, the diagnosis accuracy of the Low Scorers decreases (from 0.46 to 0.29) when they are provided with Early Warning. In this case, providing early warning of alarms did not really help and could even have the opposite effect of reducing accuracy.

4.4 Subjective Assessment through Survey

A tabulation of the final subjective assessment survey data is shown in Table 12. This provides insights into participants' views on their comprehension of the displayed information and the different aspects of the displays. More than 83% have at least a sufficient understanding of the process (Q1). Almost 87% feel that the information displayed is sufficiently easy to comprehend (Q2). Both these statistics suggest once again that the participants have sufficient background knowledge and thus are suitable for the study, just as we would expect real operators to be familiar with their process units. About 51% feel that the amount of information displayed is just nice while 41% feel that it is slightly overwhelming (Q3). Over 77% of the participants subjectively feel that the early warning of alarms provided are helpful (Q4), which further emphasizes the effectiveness of Early Warning for decision support. Both the Alarm Summary List (Q5) and the upper pane of the Alarms Display (Q6) are found to be helpful, with the former rated higher than the latter.

5. Conclusions and Discussion

Process monitoring and alarm management have seen more than 30 years of research in developing various methods and tools for decision support. Complementary to these is the human factors aspect, which is widely considered to be very important but has received significantly less attention in the PSE community. In this paper, we propose a generic experimental scheme to study the effectiveness of decision support tools from a human factors perspective. Such studies can only be achieved through experiments involving human participation. As an illustration, we have conducted a human factors experiment to evaluate the effectiveness of Early Warning of alarms. The results show that while Early Warning is effective in improving diagnosis lag and subjectively found to be helpful by the participants, it does not improve diagnosis accuracy.

There are several directions that can be explored further. The speed-accuracy trade-off is a well-known phenomenon. Humans inevitably face a trade-off between speed and accuracy when completing a task (Aperjis et al., 2011). This trade-off also seems to apply here; while diagnosis lag or speed improves with Early Warning, accuracy is slightly decreased (although not statistically significant). In this study, the participants are instructed that both speed and accuracy are important, so one is not emphasized over the other. Some participants may be naturally more inclined towards speed while others towards accuracy, which might have an effect on the study results. One way to circumvent this natural trade-off is to design a study that focuses only on one objective. For example, we could design a closed-loop study where participants can take actions based on their diagnosis to rectify the root-cause of the abnormality. In this case, the performance measure could be the duration that the plant is in the abnormal state. Both speed and accuracy are thus factored into a single performance measure.

In this study, we have assumed that the cognitive behaviors of students match those of operators. Since students may not be as experienced as operators, we have used a relatively simple case study with one process unit. The process monitoring scope of operators in the industry could be orders of magnitude larger with concomitant complexities. Performing the study on operators would thus require appropriate adjustment of the scale of the case study. This would be more challenging but would also provide stronger validation of the results. Finally, this work provides a platform for further human factors studies within PSE to balance the emphasis that has so far been on the methodology, algorithms, and the modeling aspect of decision support tools. When effectiveness of decision support is demonstrated through human factors studies, it would provide a strong selling point for industrial adoption of these tools.

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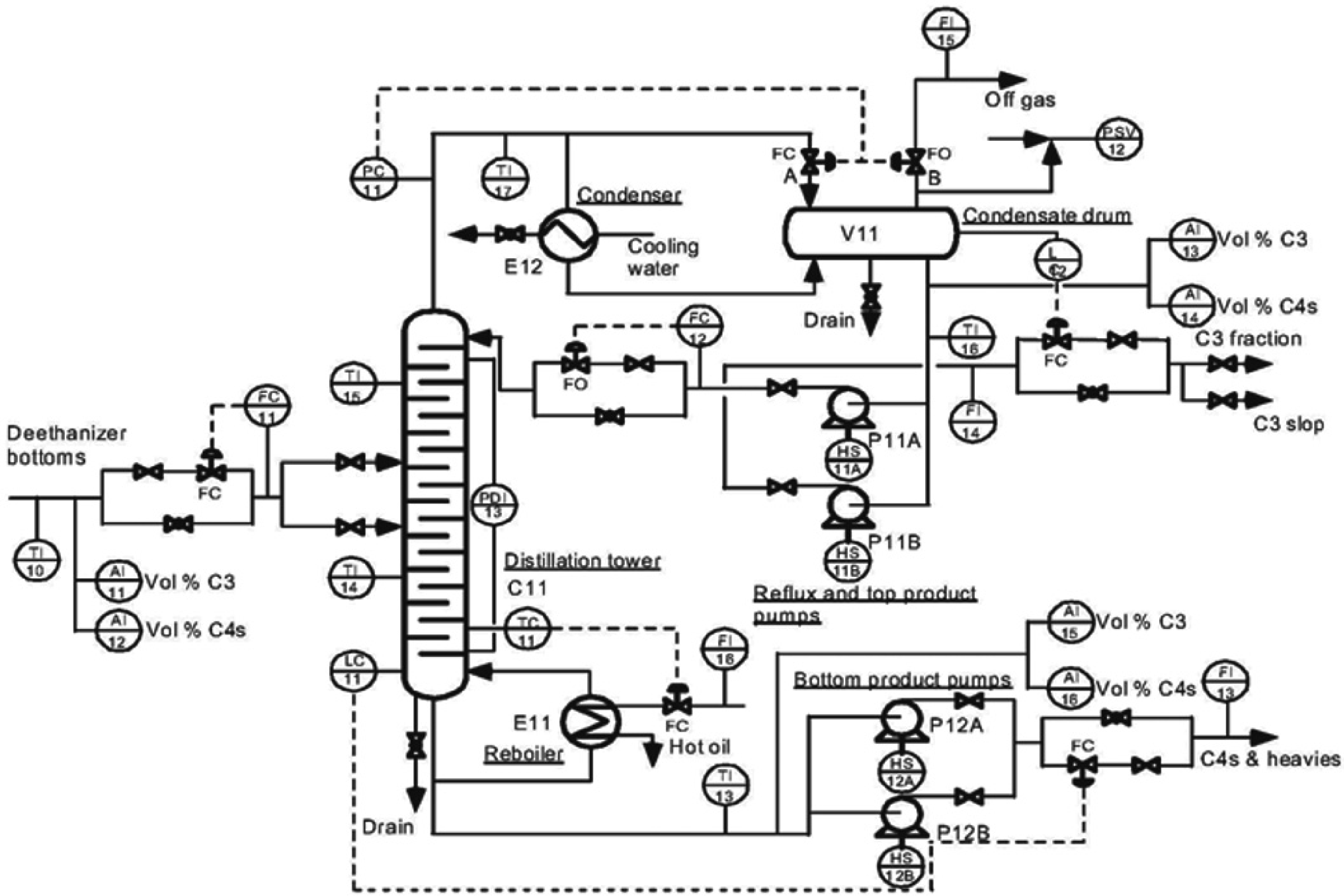


Figure 1: Schematic of the depropanizer unit (Xu et al., 2012)

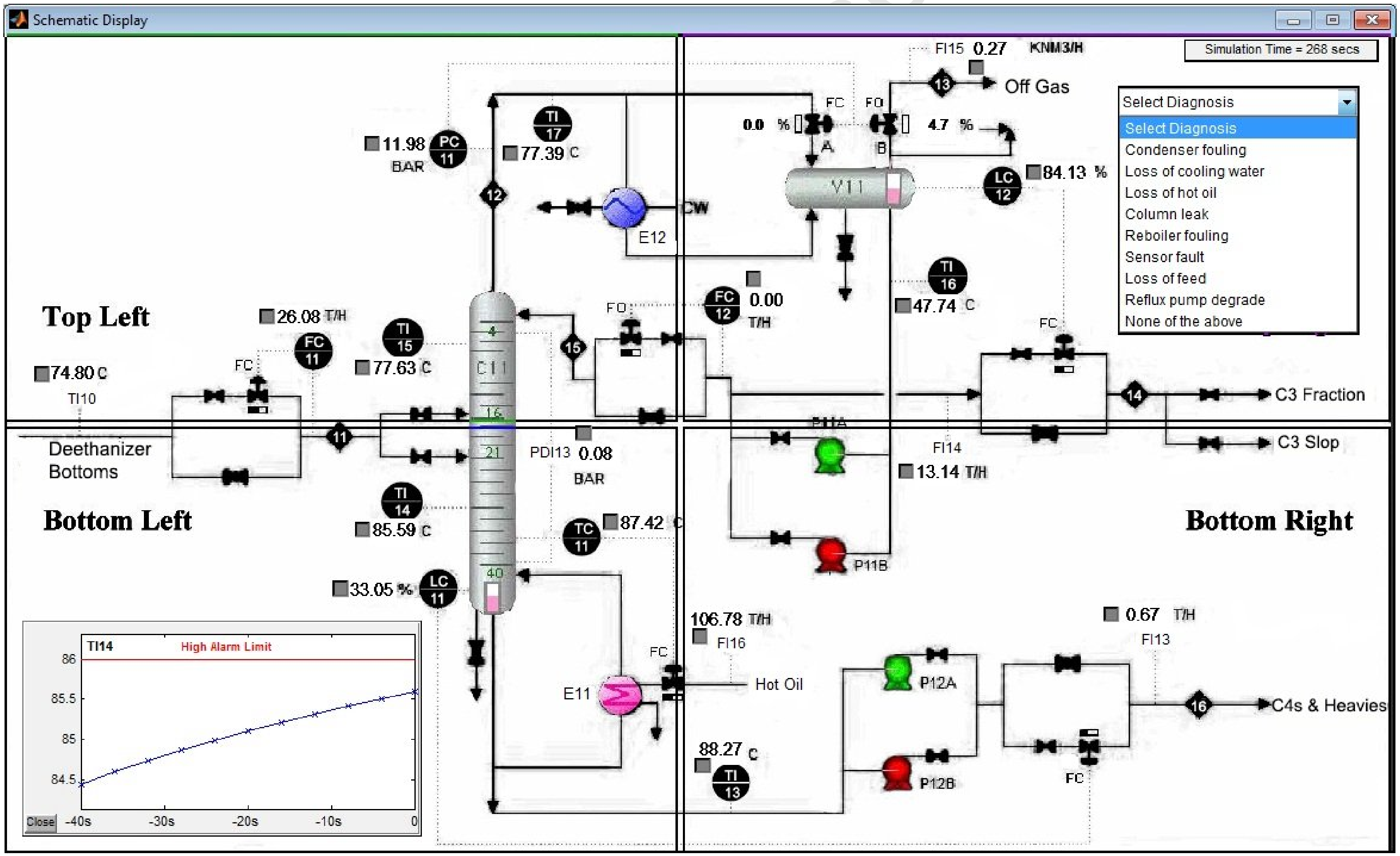


Figure 2: Schematic Display

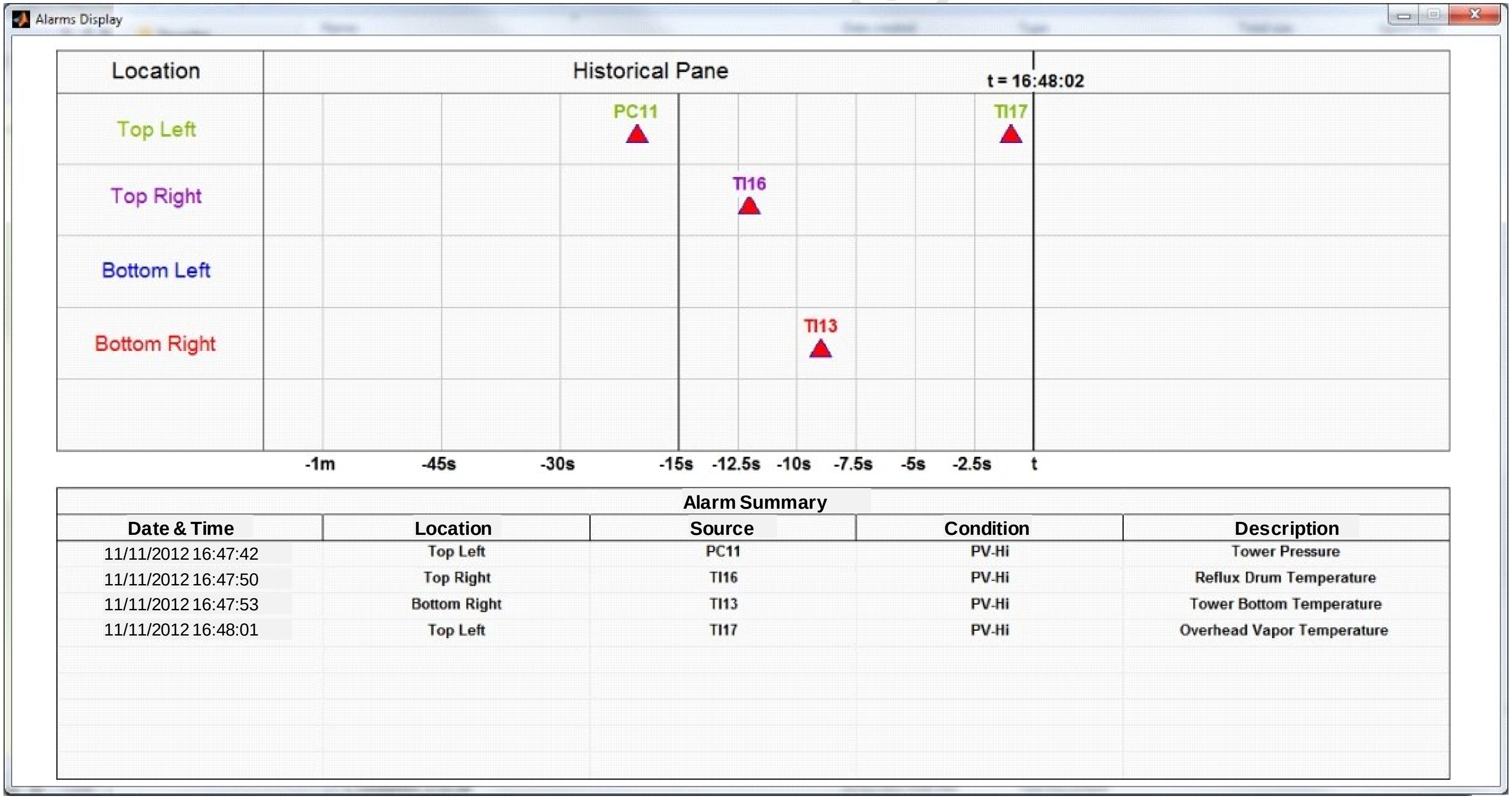


Figure 3: Alarms Display in unguided case (without Early Warning)

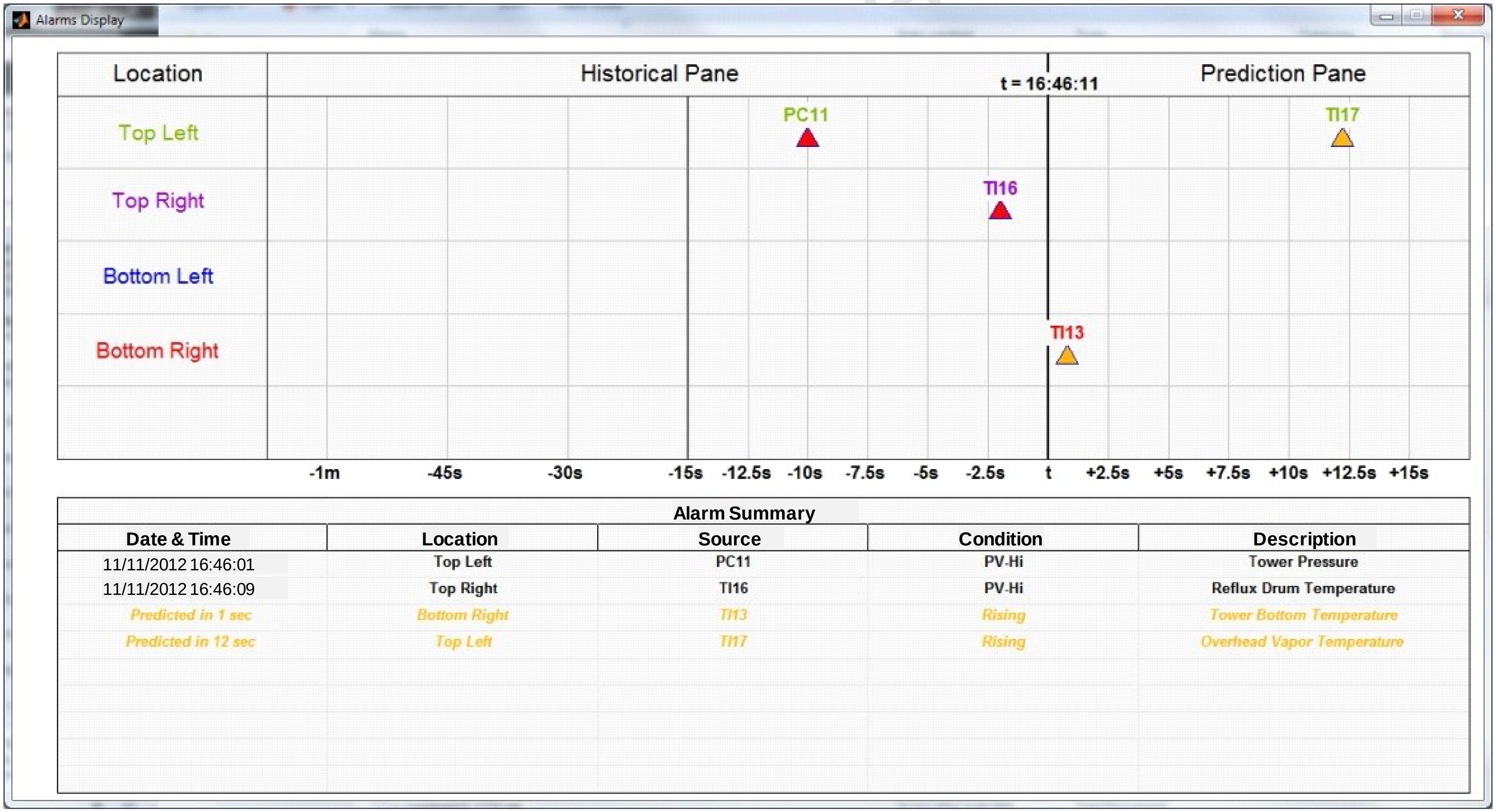


Figure 4: Alarms Display in supported case (with Early Warning)

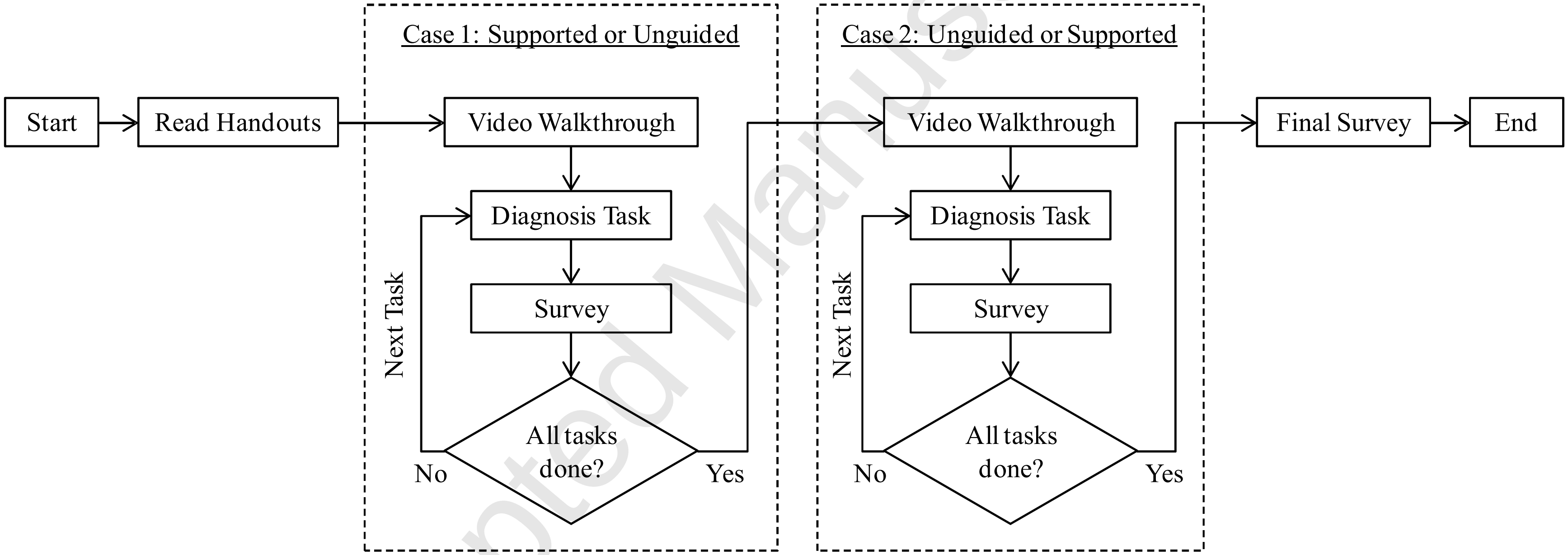
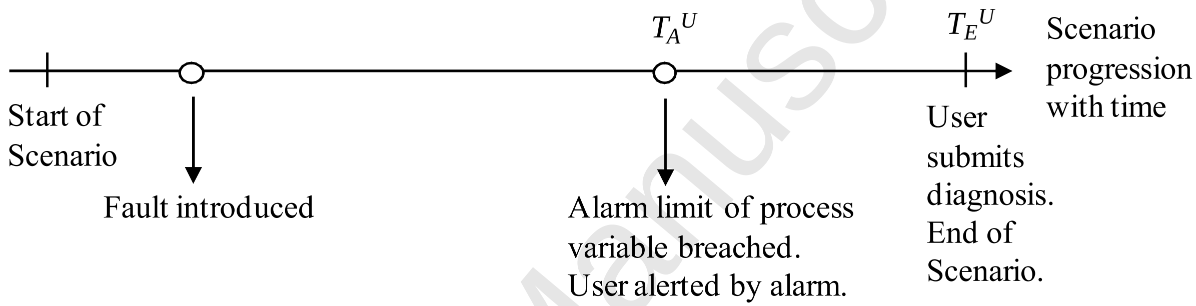
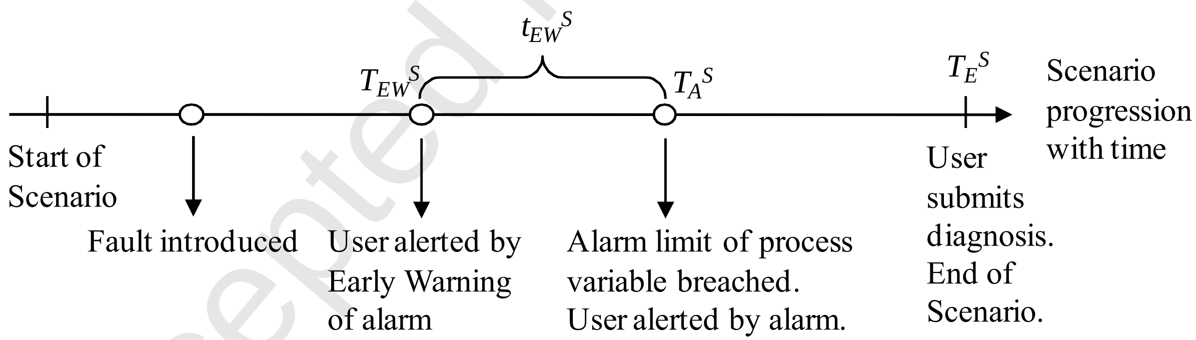


Figure 5: Study procedure

Figure 6: Participant in the midst of the study

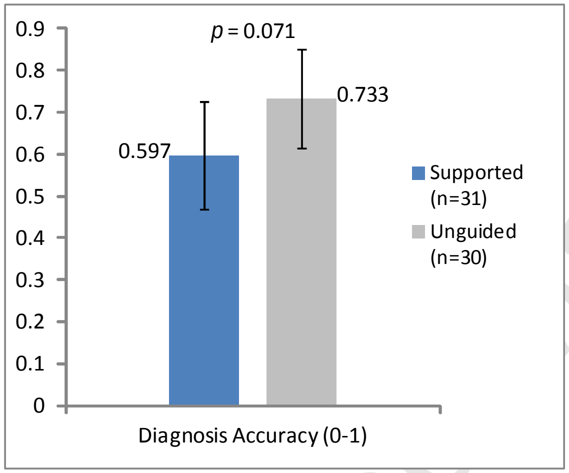


(a) Unguided case (without Early Warning)

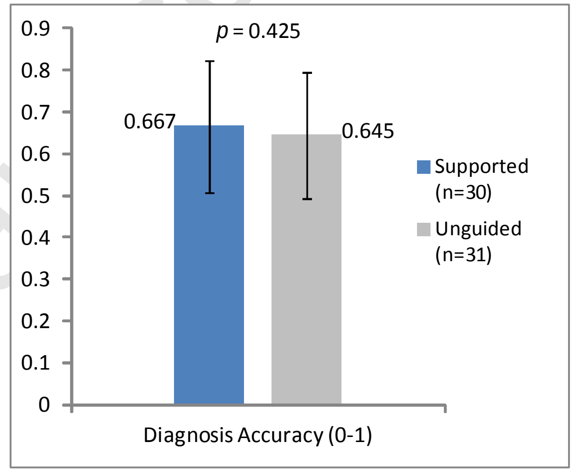


(b) Supported case (with Early Warning)

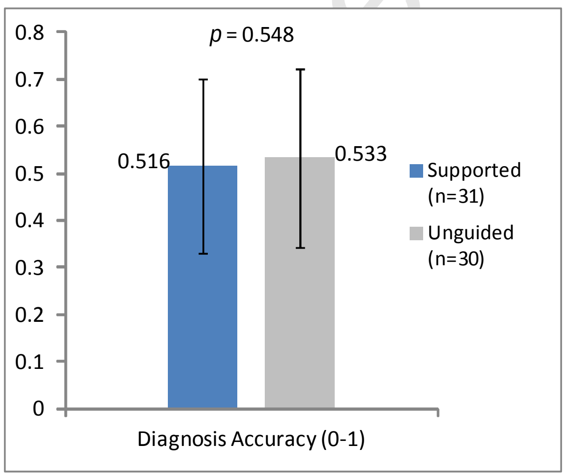
Figure 7: Breakdown of scenario progression



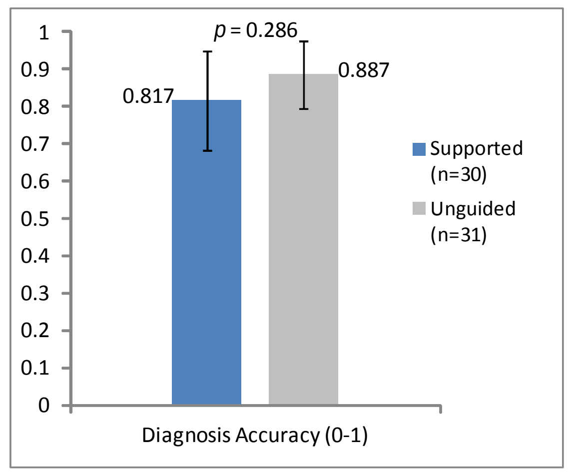
(a) Scenario 1



(b) Scenario 3



(c) Scenario 4



(d) Scenario 6

Figure 8: Diagnosis accuracy in four scenarios

Table 1: Eight alarm variables in the case study

Alarm Variable	Description
TI13	Temperature of bottom product
TI14	Temperature of tray 26 in distillation tower
TI16	Temperature of reflux flow
TI17	Temperature of top tray in distillation tower
TC11	Temperature of tray 34 in distillation tower
LC11	Liquid level in bottom hold-up of distillation tower
LC12	Liquid level in reflux drum
PC11	Pressure of distillation tower

Table 2: Sequence of alarms in the six scenarios

Scenario	Description	Alarms
1	Reflux pump degradation	TI17 HI , LC12 HI, TI16 HI, TI14 HI, LC11 LO, TC11 HI, TI13 HI, PC11 HI
2	Loss of cooling water	PC11 HI, TI16 HI, TI13 HI, TI17 HI, LC12 LO
3	Loss of hot oil	TC11 LO, LC11 HI, LC12 LO
4	Loss of feed	LC11 LO, TI14 HI, TC11 HI
5	Reboiler fouling	TC11 LO, LC11 HI, LC12 LO
6	Condenser fouling	PC11 HI, TI16 HI, TI13 HI, TI17 HI, LC12 LO

Table 3: Diagnosis Options

No	Diagnosis Option
1	Condenser fouling
2	Loss of cooling water
3	Loss of hot oil
4	Column leak
5	Reboiler fouling
6	Sensor fault
7	Loss of feed
8	Reflux pump degradation
9	None of the above

Table 4: Scoring of diagnosis accuracy

Scenario	Full Score (1)	Partial Score (0.5)
1. Reflux pump degradation	Reflux pump degradation	Loss of cooling water; Condenser fouling
2. Loss of cooling water	Loss of cooling water; Condenser fouling	Reflux pump degradation
3. Loss of hot oil	Loss of hot oil	Reboiler fouling
4. Loss of feed	Loss of feed	-
5. Reboiler fouling	Reboiler fouling	Loss of hot oil
6. Condenser fouling	Condenser fouling; Loss of cooling water	Reflux pump degradation

Table 5: Survey questions after each diagnosis task

Please rate from 1 (strongly disagree) to 5 (strongly agree)

1) I can follow the development of the process during the task.
2) I am confident of my analysis for the task.

Table 6: Final survey at the end of the study

Please rate from 1 to 5
1) I have a good understanding of the general process dynamics of the depropanizer unit. (1 = Do not understand at all; 5 = Great understanding)
2) Information displayed is easy to comprehend. (1 = Difficult; 5 = Easy)
3) What do you feel about the amount of information displayed? (1 = Barely enough; 5 = Overwhelming)
4) Has the prediction of alarms helped you in your diagnosis? (1 = Not helpful; 5 = Very helpful)
5) Was the upper pane of the Alarms Display helpful in completing the tasks? (1 = Not helpful; 5 = Very helpful)
6) Was the alarm summary list helpful in your diagnosis during the tasks? (1 = Not helpful; 5 = Very helpful)

Table 7: Task survey response

Q1. I can follow the development of the process during the task.						
Strongly disagree	1	2	3	4	5	Strongly agree
	2%	5.5%	28.5%	45%	19%	
Q2. I am confident of my analysis for the task.						
Strongly disagree	1	2	3	4	5	Strongly agree
	3.5%	16%	34%	34.5%	12%	

Table 8: Statistics for diagnosis lag in seconds

Statistics	Supported	Unguided
Number of Samples	118	120
Mean	123.96	143.97
Median	101.49	125.74
Standard Deviation	74.97	85.52
Range	307.55	360.32
Minimum	27.31	24.14
Maximum	334.86	384.46
Confidence Level (95%)	13.67	15.46

Table 9: Time advantage provided by Early Warning in the four actual scenarios

Scenario	Alarms	Alarm Time (s)	Early Warning Time (s)	Time Advantage (s)
1. Reflux pump degradation	TI17 HI	24	10	14
	LC12 HI	80	72	8
	TI16 HI	88	74	14
	TI14 HI	143	98	45
	LC11 LO	145	106	39
	TC11 HI	176	139	37
	TI13 HI	249	229	20
	PC11 HI	253	239	14
3. Loss of hot oil	TC11 LO	25	13	12
	LC11 HI	51	26	25
	LC12 LO	80	45	35
4. Loss of feed	LC11 LO	69	38	31
	TI14 HI	88	43	45
	TC11 HI	104	63	41
6. Condenser fouling	PC11 HI	29	14	15
	TI16 HI	63	35	28
	TI13 HI	89	45	44
	TI17 HI	127	92	35
	LC12 LO	141	108	33

Table 10: Statistics for diagnosis accuracy

Statistics	Supported	Unguided
Number of Samples	122	122
Mean	0.648	0.701
Median	1.000	1.000
Standard Deviation	0.425	0.400
Range	1.000	1.000
Minimum	0.000	0.000
Maximum	1.000	1.000
Confidence Level (95%)	0.076	0.072

Table 11: Comparison of high and low scorers in supported case and unguided case. Mean is shown without brackets and standard deviation within brackets.

	Statistics	High Scorers	Low Scorers
Supported	Diagnosis Score	0.94 (0.16)	0.29 (0.37)
	Diagnosis lag (seconds)	116.21 (107.19)	143.04 (77.96)
	Number of Clicks	3.81 (4.53)	3.80 (3.91)
	Percentage of Clicks on Alarm Variables	43% (34%)	70% (36%)
	Percentage of Clicks on Related Variables	79% (27%)	89% (25%)
	Number of Samples	42	40
Unguided	Diagnosis Score	0.94 (0.16)	0.46 (0.41)
	Diagnosis lag (seconds)	130.60 (94.22)	154.89 (92.63)
	Number of Clicks	4.48 (5.14)	5.75 (6.71)
	Percentage of Clicks on Alarm Variables	40% (30%)	56% (32%)
	Percentage of Clicks on Related Variables	74% (24%)	78% (27%)
	Number of Samples	42	40

Table 12: Final subjective assessment survey results

Q1. I have a good understanding of the general process dynamics of the Depropanizer unit.						
Do not understand at all	1	2	3	4	5	Great understanding
	3.3%	13.1%	44.3%	31.1%	8.2%	
Q2. Information displayed is easy to comprehend.						
Difficult	1	2	3	4	5	Easy
	1.6%	11.5%	39.3%	39.3%	8.2%	
Q3. What do you feel about the amount of information displayed?						
Barely Enough	1	2	3	4	5	Overwhelming
	0.0%	1.6%	50.8%	41.0%	6.6%	
Q4. Has the prediction of alarms helped you in your diagnosis?						
Not Helpful	1	2	3	4	5	Very Helpful
	1.6%	1.6%	19.7%	44.3%	32.8%	
Q5. Was the Alarm Summary list in the Alarms Display helpful in completing the tasks?						
Not Helpful	1	2	3	4	5	Very Helpful
	0.0%	6.6%	9.8%	36.1%	47.5%	
Q6. Was the upper pane of the Alarms Display helpful in completing the tasks?						
Not Helpful	1	2	3	4	5	Very Helpful
	3.3%	9.8%	19.7%	47.5%	19.7%	