Identification of behaviour indicators for fault diagnosis strategies

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Abstract

In manufacturing, the increasing automation leads to a rising demand for professionals fulfilling non-routine tasks like fault diagnosis of complex systems. Low reoccurrence rates of faults and working conditions, like shift work, hinder learning and make measures for knowledge support especially attractive. Additional information can be offered during the diagnosis process but the needs of the operators vary. One way to estimate the useful amount of information could be to recognize if the operator uses an associative, experience-based or an elaborate, structure-based strategy. In an attempt to identify reliable criteria to distinguish these strategies, we asked 40 participants to operate a waste water treatment simulation and confronted them with six fault scenarios. All participants received intensive training on the start-up and operation of the simulation and practiced the fault diagnosis and documentation beforehand. Through gaze behaviour analysis, a strong preference for attention focussing emerged for participants with an associative approach. Additionally, significant differences between both strategic approaches were found for Need for Cognition and prior technical knowledge.

Introduction

With the rise of cyber-physical production systems, the transformation of the workplace of human operators is proceeding (Müller, 2019). One core demand on humans in these systems is troubleshooting, or fault diagnosis. Fault diagnosis includes the detection and localisation of faults and is the prerequisite for an efficient and effective repair and a sustainable maintenance of the system (DIN EN 13306:2018-02). Typical characteristics of fault diagnosis tasks are time pressure and a low reoccurance rate of faults. At the same time the systems are characterized by a lack of transparency which makes symptoms and their cause hard to detect. An unambiguous relation between symptom and cause is rare, more often the maintenance personnel is dealing with networks of reciprocal influence and estimate probabilities for various fault causes (Bergmann et al., 1997; Rothe & Timpe 1997). In conclusion, the cognitive demands for fault diagnosis on maintenance personnel are high.

To reduce the demands of fault diagnosis, various measures can be imagined. Fault diagnosis is a knowledge-intensive task requiring declarative knowledge of the system

In D. de Waard, A. Toffetti, L. Pietrantoni, T. Franke, J-F. Petiot, C. Dumas, A. Botzer, L. Onnasch, I. Milleville, and F. Mars (2020). Proceedings of the Human Factors and Ergonomics Society Europe Chapter 2019 Annual Conference. ISSN 2333-4959 (online). Available from http://hfes-europe.org

as well as procedural knowledge of the interaction with the system and the diagnosis itself. As will be seen, different fault diagnosis strategies relate to different knowledge requirements and thus are proposed as essential indicators to inform the choice of a measure. Since recognition of different strategies is challenging, the study presented here aims at analysing behaviour correlates, specifically of gaze behaviour, to facilitate strategy recognition. To this end, two classes of strategies shall be contrasted in the following.

From a cognitive perspective, that task of diagnosis is often described in terms of reasoning and problem solving (e.g. Reed & Johnson, 1993; Schaafstal, 1993; Schmidt et al., 1990). An intensively discussed approach to describe the process of reasoning are dual-process theories. The underlying idea is the existence of two different processing types (Type I and Type II) while the specific characteristics vary between authors (e.g. Evans & Stanovich, 2013; Kahneman, 2012; Smith & DeCoster, 2000). Evans and Stanovich (2013) describe defining features of both types: Type I processes do not require working memory capacity and are autonomous, Type II processes require working memory capacity and use cognitive decoupling or mental simulation. Typical correlates of Type I processes are high speeds, parallel processing, automatic and associative thinking and experience-based decision making. Type II processes are rather slow, processing takes place in a serial, rule-based manner while thinking is more abstract and controlled. Intuitive answers are created quickly and with little effort but can be misleading, especially when reasoners lack experience. Through the intervention of reflective Type II reasoning, these intuitions can be corrected. While the insufficiency of Type I answers has been studied widely, dual-process theorists also stress the adaptivity of these answers (e.g. Kahneman, 2012). With regard to preconditions for different processing types, higher prior knowledge and experience (Smith & DeCoster, 2000) is expected to promote the use of Type I reasoning while thinking dispositions like Need for Cognition (NFC, Cacioppo & Petty, 1982; Stanovich et al., 2011) are expected to promote Type II reasoning (but see also Pennycook et al., 2017).

Critics of the dual process approach take issue with the notion of two qualitatively distinct systems and pursue a unified theoretical approach for intuitive and deliberate judgement (e.g. Keren & Schul, 2009; Kruglanski & Gigerenzer, 2011). The latter proposed a framework which states that both types of judgement are rule-based, and even can use the same rules, but vary in their difficulty of application. The theory states that rule selection depends on individual memory constrains and processing potential, the task itself and the ecological rationality of the rule. The speed and accuracy of the rule execution are controlled by individual differences of cognitive capacities (Kruglanski & Gigerenzer, 2011).

Rouse (1983) examined human problem-solving during system failures more specifically and contrasts context-specific pattern recognition with context-free search strategies. In his model of human problem solving, decisions are preferably based on state information, assessed by pattern-recognition, while structure information is included if this fails. Rouse (1983) builds on work of Rasmussen (1978) who distinguishes between symptomatic and topographic strategies. Important aspects of symptomatic strategies are the comparison with known abnormal system states; the interaction with the system is guided by previously experienced faults. A topographic search implies comparisons against a norm planned system performance which is led by the structure of the system. The use of available information can be rather uneconomic. Due to the difference in necessary prior knowledge, topographic strategies are expected to be applied when encountering unknown situations. Ham and Yoon (2007) analysed existing literature regarding the potential of principle vs. procedural knowledge to improve fault diagnosis performance and distinguish between forward reasoning “along the direction of the causalities of the circuit” (p.280), which poses higher demands, and backward reasoning. Reed and Johnson (1983) observed various expert strategies for fault diagnosis including what they termed heuristic path following. The core aspect is the focus of attention on relevant parts of the material to reduce the search space. This is in line with work by Van Meeuwen et al. (2014) who extracted three visual problem solving from the literature, namely attention focusing (i.e. focusing on relevant information in the current situation), perceptual chunking (i.e. combining elements to reduce necessary effort and ignore details) and means-end analysis (i.e. starting from the goal working backwards). They could show differences in the eye movements between novices, intermediates and experts in the number of fixation, fixation duration, number of transitions and time to first fixation in accordance to their hypotheses. In specific, experts showed more perceptual chunking and followed less a means-end strategy. Also, they reduced the amount of information more strongly than other groups.

Taken together, behaviour during fault diagnosis can be classified roughly into two classes: (1) a more associative, experience-based approach which is based on information reduction and includes pattern-recognition, and (2) a more elaborate, structured approach which is based on information exploitation. While no clear predictions regarding the fault diagnosis success can be made, cognitive and knowledge demands are expected to vary between theses approaches and influence strategy choice.

In the following, an empirical study will be presented which confronted participants with a fault diagnosis task to elicit the application of individual strategies and analyse behaviour correlates. After outlining the design and method of the study, detailed hypotheses will be introduced and tested. Finally, conclusions will be drawn and discussed as to which behaviour correlates are associated with either the associative, experienced-based approach or the elaborate, structured approach to fault diagnosis.

The study

Design

The aim of this study was to investigate behavioural correlates of fault diagnosis strategies, especially in gaze behaviour. To this end, the process control simulation WaTr Sim (waste water treatment simulation, Urbas & Heinath, 2007) was employed. In the first part of the study, all participants underwent a training for the start-up and operation of WaTr Sim as well as the procedure of fault diagnosis and reporting. In the second part of the study, participants were entrusted with the task of operating the simulation during nine simulated production weeks and asked to report and diagnose all faults that might occur during this time. The behaviour of the simulation was controlled by nine scenarios of which six contained faults. The order of the fault scenarios was randomized except of the final one. Behavioural data was gathered throughout all nine productions weeks via eye tracking, screen and interaction recording as well as subjective questionnaires. In this contribution, the focus lays on the final production week, the analysis follows a between group approach.

Participants

The present study included 40 volunteers of which ten had to be excluded because of technical issues (n=4), insufficient training performance (n=1) and failure to detect the fault during the last production week (n=5). Participant acquisition took place in the university's environment. The remaining sample consisted of 19 men and 11 women with an average age of M = 27.2 (SD = 8.6). Twelve participants practised a profession, 17 were students, one was unemployed. Most participants (n=20) had no prior knowledge on the task of fault diagnosis while six had high to very high prior knowledge (M = 2.1, SD = 3.5, 9-point Likert scale). Additionally, prior knowledge in related technical fields was assessed via a 9-point Likert scale (1 = none, 9 = excellent). The results show moderate technical knowledge (M = 4.1, SD = 1.7). All participants had no prior knowledge of the simulation WaTr Sim before the study and were compensated at the end of the study in the amount of €20.

Materials

WaTr Sim
WaTr Sim (Urbas & Heinath, 2007) simulates a waste water treatment facility with waste water feeding in via truck deliveries and multiple stages of processing taking place until fresh water and a purified gas is produced. Altogether six stages can be distinguished: delivery, homogenisation, separation, an intermediate product repository, gas scrubbing, and a final product repository (see Figure 1, from top-left to right). While the first four stages and the sixth stage included automatic functions for information acquisition and analysis (cf. Parasuraman, Sheridan & Wickens, 2000), mainly via an alarm function based on tank level thresholds, the fifth stage is fully automated when quality of production and valves settings of the previous stages are within the normative range.

Operators are responsible for the start-up of the facility and a safe and efficient production, which maximises the amount of fresh water and purified gas and minimises the amount of waste produced. The interface allows, inter alia, for adjustments of set points of valves and heating systems and offers detailed views of component groups, information on current alarms and a trend visualisation for the final product. Fig. 1 shows the main control interface. Each run of the simulation consists of one production week with a predefined length measured in simulation steps. Each step lasts 2000ms.

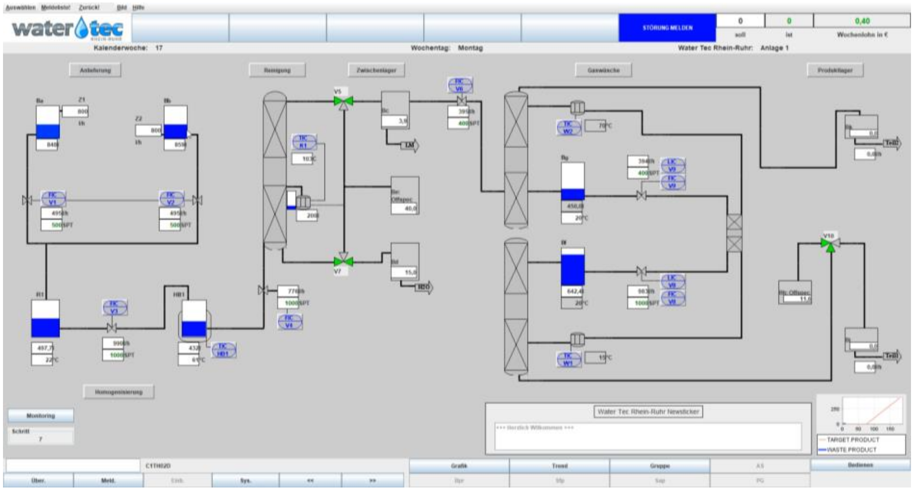

Figure 1. Screenshot of WaTr Sim with valves (e.g. V1, V6), heaters (e.g. H1, W1) and tanks (e.g. Ba, Bc).

Scenarios

The operation of the simulation was predetermined by nine scenarios: three control scenarios and six fault scenarios. The scenarios defined all set points at the first simulation step and lasted for either four or six minutes. Faults included fully and partially defective units and were visible through component observation, system alarms and/or a news ticker. For example, in the last scenario the heating unit of the gas scrubber fails, the output only reaches a temperature of 50°C instead of 70°C.

Training

The training for operating the simulation WaTr Sim followed the principles of instruction (Merrill, 2002) and was guided by a handbook presented on a 10.8” tablet. All participants were trained to execute a specific start-up procedure; they gained knowledge on all components and their functionality and practiced the interaction with the interface and the fault report. The training was led by the experimenter who followed standardized instructions for the interaction with the participants. It concluded in two knowledge tests, one written test on declarative knowledge regarding the facility and one practical test on start-up, operation and fault diagnosis of the facility. Passing these tests was a prerequisite for participating in the second part of the study. Altogether, the training lasted about 60min.

Data Acquisition

Eye Tracking

The experiment took place at the institute’s lab rooms with illumination held constant. The simulation was presented on a 24” LCD screen at a resolution of 1920x1080pi. Eye movements were recorded using an EyeLink 1000 Plus desktop eye tracker in head-free mode at a sample rate of 1000Hz (accuracy: 0.25-0.5°, spatial resolution: 0.05). Parsing of eye data followed default thresholds. Participants were calibrated with a 9-point-calibration which was checked before every production week with a drift assessment and repeated if the deviation was 1° visual angle or higher.

Questionnaires

The study included multiple questionnaires, inter alia to assess demographic data, and prior knowledge, and a German version of the short scale on Need for Cognition (NFC, Beißert et al., 2014).

Fault report

Participants were instructed to report each fault after detection via a button implemented in the simulation before they began searching for the cause. Description of the fault was done after the production week had finished.

Think-aloud interview

After the last production week, the screen recording of this week was replayed for the participants and an interview following the think aloud method was conducted and recorded. During the interview, participants were encouraged to report on their actions and thoughts with questions from an unstructured interview guideline (e.g. *"What are you doing at this moment?"* or *"Please describe your thoughts in more detail."*).

Data analysis

Statistical analysis was conducted with R (R Core Team, 2018) and a significance level of α=.05. For directional hypotheses, one-tailed tests were used. The data was tested on deviation from normal distribution with the Shapiro Wilk test for each group. In case of a detected deviation, Wilcoxon rank sum tests were employed instead of t-tests for independent samples. Because of unequal group sizes, the effect size was calculated with Hedge's correction.

For the analysis of eye tracking data, the screen was divided into multiple areas of interest (AOI) including the processes of delivery, gas scrubber and final repository as well as separate components and information sources. As the size of the areas varied, parameters like number of fixations (n_{fix}) and fixation duration (t_{fix}) were normed on the size of the current AOI. Eye movement data was included for a 30s time window before the fault report via button press.

Recordings from the interviews were transcribed and, based on a guideline with category descriptions and examples, categorized into two classes of strategies: (1) an associative, experienced-based approach which is based on information reduction and (2) an elaborate, structured approach which is based on information exploitation. To ensure reliability, a third of the material was categorized by two raters. The agreement of the raters was acceptable with Cohen's $\kappa = 0.61$. In a second step, participants were assigned to two groups (associative vs. elaborate) depending on the ratio of statements in each category.

Accuracy of diagnosis was evaluated on a scale from 0 to 3 with a grading scheme including the ratio of the number of correctly vs. incorrectly identified symptoms and the correctly identified cause of the fault.

Hypotheses

Building on the insight of existing research, multiple hypotheses were deduced (Table 1).

Table 1. Overview over hypotheses

<table>
<tr><th></th><th>hypotheses</th><th></th><th>assessed behaviour indicators</th></tr>
<tr><td rowspan="6">Participants with an associative approach show…</td><td>…lower or higher NFC (H1)…</td><td rowspan="6">…than participants with an elaborate approach.</td><td>sum NFC scale</td></tr>
<tr><td>…lower or higher prior technical knowledge (H2)…</td><td>sum prior technical knowledge</td></tr>
<tr><td>…more attention focussing (H3)…</td><td>n_{fix} on delivery lower
t_{fix} on delivery lower
t_{fix} on tank Bk lower</td></tr>
<tr><td>…more backward reasoning (means-end) (H4)…</td><td>more saccades to the left (sum)
n_{fix} on final repository higher
t_{fix} on final repository higher</td></tr>
<tr><td>…more perceptual chunking (H5)…</td><td>lower number of components fixated</td></tr>
<tr><td>… no difference in fault diagnosis performance (H6)…</td><td>accuracy of diagnosis equal</td></tr>
</table>

Results

The strategy classification resulted in two unequally sized groups, 13 participants followed an elaborate approach while 17 followed an associative approach.

In Table 2, results for all dependent variables are summarized. In accordance with H1, there is a significant difference between groups on NFC (t=3.948, df=16.7, p=.001, 95% CI [-9.2, -2.8]). Figure 2 visualises the result. Participants with a more associative approach showed a higher NFC than participants with a more elaborate approach. The effect is large ($g_{Hedge's}$=-1.5). H2 can be accepted as well with participants with an associative approach showing higher prior technical knowledge than participants with an elaborate approach (W=44, p=.006, 95% CI [-2.9, -0.4], see figure 3). The effect is large ($g_{Hedge's}$=-1.8). Additionally, the results show strong support for H3, but only limited support for H4 and no sppurt for H5. There was no significant difference between groups regarding the diagnosis performance (W=131, p=.250, 95% CI [-2.0, 0.0], the effect was small ($g_{Hedge's}$=-0.5). Figure 4 visualises the data. The implications will be discussed in the following chapter.

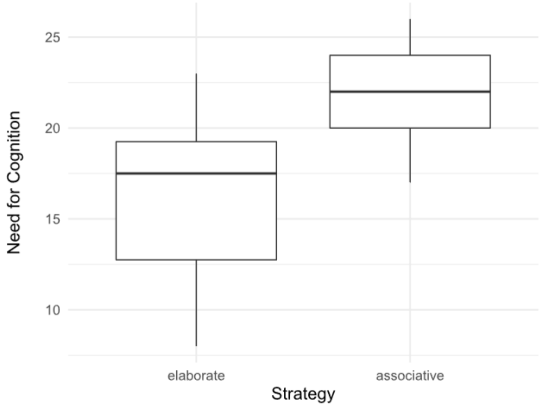

Figure 2. Box-Whiskers-Plot for Need for Cognition.

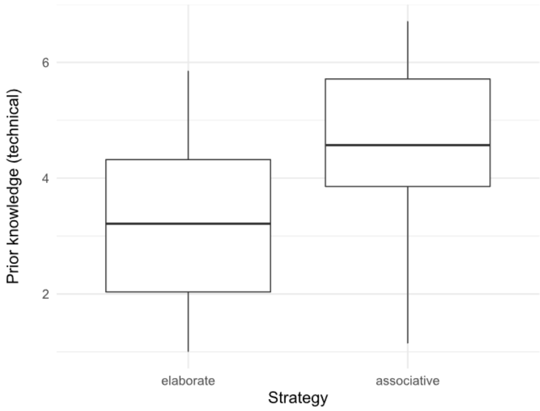

Figure 3. Box-Whiskers-Plot for prior technical knowledge.

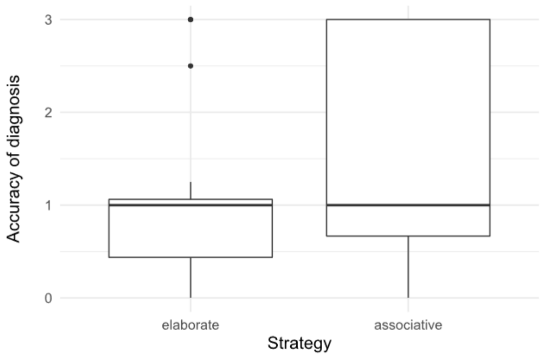

Figure 4. Box-Whiskers-Plot for accuracy of diagnosis.

Table 2. Overview over results

hypothesis	*dependent variable*	*t (df) / W*	*p*	*95% CI*	$g_{Hedge's}$
H1	sum NFC scale	t=3.948, df=16.7	.001	-9.2, -2.8	-1.5
H2	sum prior technical knowledge	W=44	.006	-2.9, -0.4	-1.8
H3	n_{fix} on delivery	W=78.5	.002	0.4, ∞	1.7
	t_{fix} on delivery	W=85	<.001	204.3, ∞	2.2
	t_{fix} on tank Bk	t=2.100, df=4.4	.049	5.6, ∞	1.4
H4	Sum saccades to the left	t=-0.663, df=26.7	.744	-4.6, ∞	-0.2
	n_{fix} on final repository	t=1.479, df=22.5	.076	-0.1 ∞	0.5
	t_{fix} on final repository	W=130	.045	5.2, ∞	0.6
H5	Number of components fixated	t=0.640, df=25.6	.264	-1.8, ∞	0.2
H6	Accuracy of diagnosis	W=131	.250	-2.0 , 0.0	-0.5

Discussion and conclusion

The aim of this study was to investigate behaviour correlates of fault diagnosis strategies. Based on a review of existing theory and research, two classes of strategies have been defined: an associative, experienced-based approach and an elaborate, structured approach. Participants were split into these two groups based on a content analysis of verbal reports.

The results show large and significant differences between participants from both groups before the study, supporting the claim that strategy choice is influenced by individual differences of prior knowledge and motivation (e.g. Stanovich et al., 2011; Kruglanksi & Gigerenzer, 2011). It should be noted that all participants had no experience with the operation of WaTr Sim before the study and were exposed to the same scenarios – the knowledge gain during the study was thus dependent on the individual learning performance.

With regard to attention focussing, the results strongly support the hypothesis, that an associative approach includes higher attention focussing. Participants with an elaborate approach spend more time fixating components of the first step of the process. Also, they fixate this step more often. During the final scenario, only parts of the gas scrubber and the final repository showed symptoms of the faults. Such behaviour can be understood as a more thorough use of information with the gaze being diverted from the more obviously affected components. This is also true for the tank Bk which is part of the final repository – in past scenarios, analysis of the tank's behaviour was not necessary for the fault diagnosis. Therefore, participants with an associative approach were not expected to spend attention on this component as experience taught them it is not necessary. The results agree with this expectation as participants with an elaborate approach spend more time fixating tank Bk.

Backward and forward reasoning have been mentioned by various researches to describe diagnosis strategies, e.g. the topographic search described by Rasmussen (1978) which includes searching systematically through the system and which can be classified as elaborate approach. The results show that participants with an associative approach spend more time on the goal state of the system but there is only a marginal difference in the number of fixations on the goal state and no difference in the number of gaze switches to the left vs. to the right. Taken together a preference for means-end analysis seems to exists within the associative approach but the direction of the reasoning stays unclear.

As chunking includes grouping of elements, the expectation was to find participants with an associative approach fixate less components but instead choosing representative components for different parts of the process. This expectation was disappointed. Possible reasons included insufficient training on the system as chunking is especially seen within experts (van Meeuwen et al., 2014).

Various authors stress the claim that success of strategies depends on the task at hand and the performing individual, therefore a superiority of one class of strategies was not expected and also not found. Accordingly, Figure 4 shows equal medians in both groups, but a striking difference in the variance of the data. To understand this result better, analysis of supplementary data will be necessary.

In conclusion, participants differed meaningfully in their attention focussing according to their strategic approach. Individual differences of motivation and prior knowledge seem to play an important role for strategy choice. To understand this relationship better, more insights on strategy development over time and specific use of knowledge are necessary. Nevertheless, the distinction between an associative and an elaborated approach has been proven useful and behaviour indicators emerged.

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