Validating an Abnormal Situation Prediction Model for Smart Manufacturing in the Oil Refining Industry

Abstract

The main objective of this research was to validate a mathematical model for the predictivity of refinery operators' abnormal detection behaviors. Moreover, we examined operators' visual behaviors in response to abnormal situations at different ages and with different task load, task complexities, and input devices. We found that participants had lower mean fixation durations and fixation/saccade ratios when they were in the condition of a touchscreen device. Moreover, we found that older adults had higher mean saccade durations and saccade amplitudes when they were in the condition of a touchscreen device. Finally, the mathematical model was found to be generalizable to different task loads and age groups. Our results show that visual behaviors can indicate specific internal states of participants, including their cognitive workload, attention, and situation awareness in a real-time manner. The findings provide additional support for the value of using visual behavior to assess responsiveness of oil refinery operators and for future applications of smart manufacturing monitoring systems.

1. Introduction

Smart manufacturing is transforming the oil refining sector into a connected, information-driven environment. To optimize production in the oil refining industry, researchers use various methods such as a machine-learning-based digital twin, Big Data, and Artificial Intelligence (Hassani & Silva, 2018; Mao et al., 2019; Min et al., 2019). Interconnections among human beings, objects, and systems are key components of the dynamic real-time optimization of

Industry 4.0, which emphasizes the role of human beings in a smart manufacturing economy (Bahrin et al., 2016).

In the oil refining industry, human operators are required to monitor the states of different types of gauges (e.g., flow, level, pressure) in a control room and to detect abnormal situations immediately to avoid plant incidents. Reduction of safety incidents in oil refining industry should be the first critical step in abnormal situation management (ASM) for smart process manufacturing. However, operators sometimes have difficulty detecting abnormal situations immediately, and human failures account for 80% of such accidents as the failure of the regulator system (Abílio Ramos et al., 2017; Kariuki & Löwe, 2007; Zarei et al., 2017). To evaluate operators' abnormal detection performance of human operators, various types of tools have been used, such as reaction time, abnormal detection accuracy, and Human Reliability Analysis (Abílio Ramos et al., 2020; Noah et al., 2014).

Besides behavioral measures, human visual behaviors have the sensitivity and specificity to provide a broad picture of operators' internal states such as cognitive workload, attention, and situation awareness (SA). In the current study, we validated a statistical model that predicts the timeliness with which an operator's visual behaviors respond to abnormal situations in an oil refinery operating room. Moreover, we explored the effects of age, input device, task load and complexity on operators' internal states. This study can give insights on improving production as well as reducing safety incidents in the oil refining industry. We also provide suggestions for future interface design tailored to operators at different ages to create a better individualized and connected environment.

The rest of this paper is organized as follows. The remaining part of Section 1 gives the background for and an overview of the present study. Section 2 describes the methodology, including the experimental design and data analysis. The results are presented in Section 3 and discussed in Section 4. We conclude the paper in Section 5.

1.1. Performance measurements in the detection of abnormal situations

The behaviors of operators when detecting abnormal situations in oil refinery control rooms can be attributed to factors including operators' characteristics (e.g., age) and control room environments (e.g., task load, task complexity, input device) (Bourdouxhe et al. 1999; Buddaraju 2011; Noah et al. 2014; Noah et al., 2017). To quantify how these factors influence detection behaviors, existing studies have mainly focused retrospectively on detection behaviors of abnormal situations. Two main measures of behaviors are reaction time and detection accuracy. For example, Noah et al. (2014) evaluated three surface chart displays in an oil refinery and found that the surface chart display was superior to the others in response time and accuracy in detection of gauge state changes. More recently, Noah et al. (2017) measured operators' response time to abnormal events and illustrated that the 4K-keyboard condition resulted in faster Detection + Navigation time than the 4K-touchscreen condition.

While these behavior metrics quantify operators' oil refinery control behaviors, they have the following limitations. First, behavior metrics capture operators' overall behaviors after a task has been completed, but they do not capture the trajectory of an entire sequence of behaviors as a consecutive time-series. Second, although operators might not exhibit observable changes at the performance level, their cognitive states might be significantly altered and should be included in measures of their overall detection performance. Subjective self-reported measures can be used to assess operators' internal states. However, self-reporting of internal states often conflicts with objective measurements, compromising its accuracy (Endsley 2019). One solution to this problem is to collect operators' visual behaviors to examine their workload, attention, and SA, synchronically and continuously.

1.2. Visual behavior measurements in oil refinery research

With the advent of low-cost and non-invasive eye-tracking devices, one can collect operators' visual behaviors to reflect their cognitive states as affected by age, task load, task complexity, and input device. Commonly used measurements of visual behaviors in oil refinery research include fixations, saccades, and pupil size.

Recently, fixation duration and fixation numbers have been used in oil refinery studies (Huang et al., 2019; Salehi et al., 2018; Shi et al., 2021). Researchers have shown that number of fixations could be effective and continuous indicators of workload in a control room monitoring task (Huang et al. 2019). Moreover, Salehi et al. (2018) compared novices' and experts' visual behaviors captured in real-time monitoring when they were engaged in a task with regard to abnormal situation. They found that experts had better SA for higher fixation duration and higher fixation numbers in situations of significant drill pipe pressure variation.

Saccade duration has the sensitivity to assess operators' cognitive processing (Das et al. 2018). For example, Das et al. (2018) compared differences in saccade duration between consistent events (e.g., operators manipulating the same variable over a large time window) and inconsistent events. They found that saccade duration increased when the case study participant performed an inconsistent action, which could be attributed to increase in cognitive processing when the participant decided to take a different action. To our knowledge, saccade amplitude has not been measured in a petroleum plant. However, air traffic control researchers measured saccade amplitude in relation to monitoring tasks and found that saccade amplitude decreases as mental workload increases (Li et al. 2018).

Pupil size is used to measure operators' cognitive workload in the control room (Bhavsar et al,, 2016; Kovesdi et al., 2018; Srinivasan et al., 2019). For example, Bhavsar et al. (2016) measured the diameter of control room operators' pupils in real time during operations and found that pupil diameter was a good indicator of cognitive workload during the execution of tasks. Fixation/Saccade ratio has not been used in petroleum plant studies. We include this measure because it reflects the ratio of processing time divided by target-searching time (Holmqvist et al. 2011).

Previous studies on operators' responses to abnormal situations mainly focused on performance measures such as accuracy and response time. Little is known about the effects of operators' cognitive load, attention, and SA during abnormal situations, which can be assessed through visual behavior measurements. In addition, studies that reported the visual behaviors of operators in petroleum plants (Salehi et al. 2018; Srinivasan et al. 2019) did not focus on the visual behavior of operators in abnormal situations in terms of such factors as age, task load and complexity, and input devices, which were examined in this exploratory study. Visual data collected included fixation duration, fixation number, saccade duration, saccade amplitude, fixation/saccade ratio, and pupil size.

1.3. Modeling operators' behavior

As the nature of manufacturing work is changing and imposing greater cognitive demands, there is a need to develop system models for measuring and predicting human performance in repetitive task operations (M. Abílio Ramos et al., 2020; Bommer & Fendley, 2018; Conati & Merten, 2007; Loboda, Brusilovsky, & Loboda 2010). For example, Bommer and Fendley (2018) presented a theoretical framework to measure mental workload in an Air Force MATB task. They used NASA-TLX, Workload Profile, fixation duration and human error probability to build a mathematical model that predicts workload peaks accurately. Moreover, Loboda et al., (2010) demonstrated that eye movement data improves the on-line assessment of user meta-cognitive behavior. They found that gaze-based measures show that adaptive visualization activates attention more than its non-personalized counterpart and is more interesting to students.

Existing studies featuring modeling of operators' behaviors have combined performance measurements (e.g., NASA-TLX) and visual behaviors, which fails to reflect operators' internal states in real-time (Bommer & Fendley, 2018). Moreover, the accuracy of prediction using visual behaviors is less than 70% (Bednarik et al., 2013). Therefore, a model that measures operators' internal states in real time and has high prediction accuracy is needed. In a paper in the book, *Human-Automation Interaction* (in press), we present a statistical model using fixations and saccades to predict the cognitive workload of the petroleum control room operators, which has over 95% accuracy. In the present study, we investigated if this prediction model can be applied to a population comprising different ages and a task with different task loads. We simplified the oil refinery monitoring task to ensure that participants focused only on the states of the gauges while monitoring without being distracted by the confounding elements of real interfaces. This design helped us to better quantify and understand operators' internal states in detection of abnormal situations.

Overall, our aim in this study was to investigate (1) the effects of input device and age on visual behavior; (2) if the visual behavior can reflect task complexity and load; and (3) whether the mathematical model can be generalizable to different age groups and task loads.

2. Method

2.1. **Participants**

Thirty participants were recruited: 15 younger (20-30 years old) and 15 older (55-65 years old) adults). They were paid $25 each.

2.2. Experiment design

A four-factor (age, task complexity, task load, and input device) experiment with repeated measures on three factors was designed. In this design, each participant was measured at all levels of task complexity, task loads and input devices. Thus, each participant performed eight trials to accommodate all levels of the factors considered. A pilot study was conducted before the formal experiment to decide the levels of task complexity and load. Two gauge types selected to represent low and high task complexity (Figure 1) were flow and mixed (a mixture of level, pressure, flow and temperature). Each participant underwent two levels (low and high) of task load, which was defined in terms of the total number of abnormal situations that operators manage within a given time period. The total number of abnormal events in a high task load scenario is five times as large as in a low task load scenario. The input devices were touchscreen (direct input device) and mouse (indirect input device). All subjects performed the same set of scenarios, and the order of the treatments was randomized. Each trial in the eight-trial experiment, called an abnormal detection task, lasted for four minutes. Before the abnormality detection task, participants were given recognition training to ensure that they could recognize the gauges accurately and quickly.

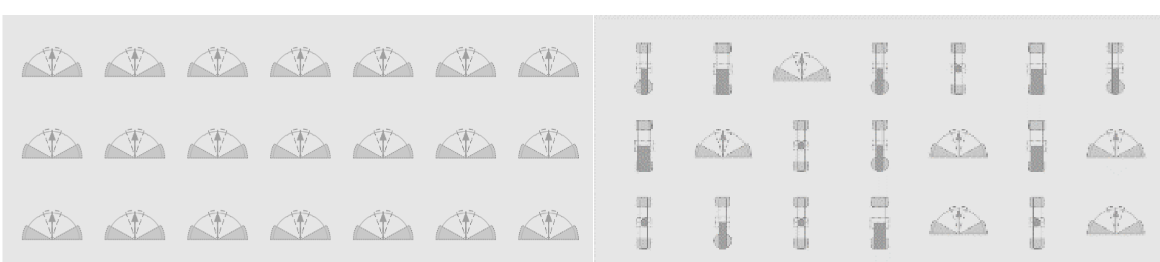

Figure 1: Examples trials of flow (left) and mixed gauges (right)

2.3. Apparatus

The study was conducted on a standard PC (Windows 10 installed), and a 23.8" monitor that was set to a resolution of 1600×900 pixels. An eye-tracker (Tobii X3-120) was used for recording the participants' gaze data at a sampling rate of 120 Hz.

2.4. Dependent measures

Table 1 lists all the visual behavior measurements used in this study.

Table 1. Dependent measures.

Eye-Tracking Metric	Definition
Mean fixation durations	Mean duration of fixations.
Mean saccade durations	Mean durations of saccades.
Mean saccade amplitudes	Mean distance travelled by a saccade from its onset to the offset.
Fixation/Saccade ratios	Comparison of search time to processing time.
Total fixation numbers	Number of times the subject fixated on the screen.
Mean Pupil Size	Pupil diameter or area

We calculated the above-mentioned statistical measures using time windows during the abnormal situations. Each abnormal event was approximately 23 seconds long, beginning when the pointer of a gauge falls above or below the normal level and ending when the pointer returned to the normal level. Each low task load trial has four non-overlapping abnormal events within four minutes, while each high task load trial had 20 abnormal events with overlaps among them.

2.5. Procedure

Prior to arrival, the participants completed an online demographic questionnaire to confirm that they had normal or corrected normal vision. Upon their arrival, they were asked to sign consent forms, and then they participated in practice trials to ensure that they were able to recognize the gauge types and gauge states (normal, abnormal and alarm) quickly and accurately. Next, the participants started the experiment by pressing the SPACE button, and a screen with one of the randomly chosen eight trials appeared. Four trials were finished by touchscreen and four trials were finished by mouse. In each trial (Figure 2), the participants were asked to click on the gauge if it was abnormal. Finally, they were paid and excused from the experiment.

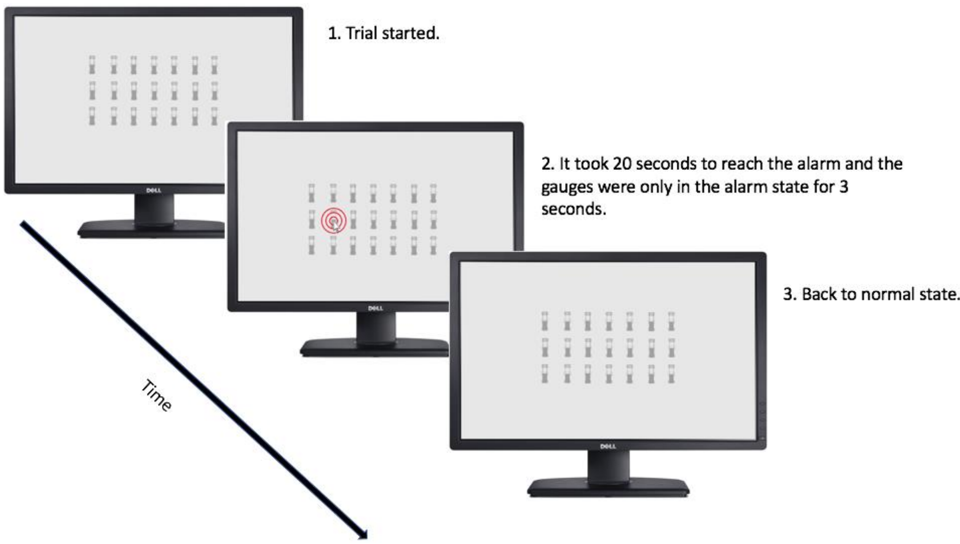

Figure 2. An example of the alarm state.

2.6. Data analysis

As noted, each participant completed eight trials, yielding a total of 240 trials among 30 participants. Due to some malfunctions during the simulation task, 41 trials were excluded, leaving 199 trials for analysis. A generalized linear mixed model (GLMM) was conducted using SPSS version 26 to examine effects on continuous dependent variables (Table 1). The age, task complexity, task load, and input device were used as fixed effects, and participants were treated as random effects to resolve non-independence in the model. The GLMM is robust against violations of assumptions of normality (Kachman 2000). The significance level alpha was set at .05. Next, a logistic regression model was applied to predict abnormal situations and validate the generalizability of our statistical model, which was introduced in our chapter of the book *Human-Automation Interaction* (in press). The logistic regression model used the Logit P(x) values calculated by plugging the numbers into the formula as the predictor. Our resulting model is:

3. Logit P(x) = log [P(x) / (1− P(x))] = ln [P(x) / (1− P(x))] = 1.382740e-01 - 2.977335e-03 total fixation numbers + 2.314954e-05 total fixation durations -3.351016e-02 fixation/saccade ratio - 2.668184e-03 fixation duration means + 2.659500e-05 total saccade durations - 2.274302e-02 saccade duration means + 9.710600e-02 saccade amplitude

Results

Input Device

During abnormal events, there was a significant main effect of input devices on mean fixation durations (F (1,198) = 18.979, p < .001). Participants had lower mean fixation durations when they were in the condition of touchscreen device (Figure 3).

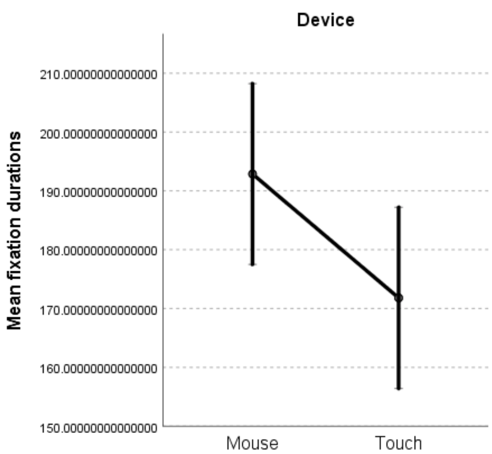

Figure 3. Mean fixation duration by input device.

During abnormal events, there was a significant main effect of input devices on fixation/saccade ratios (F (1,198) = 19.642, p < .001). Participants had lower fixation/saccade ratios when they were in the condition of touchscreen device (Figure 4).

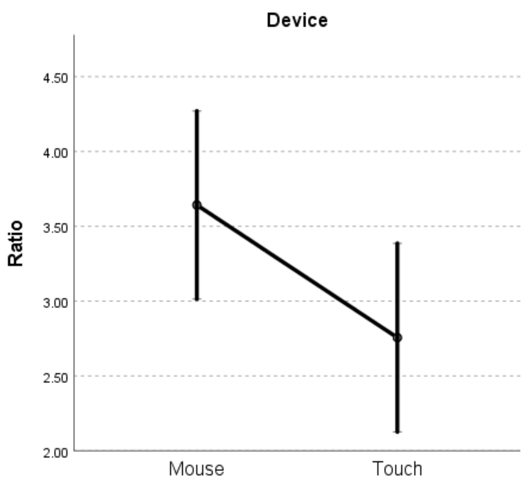

Figure 4. Fixation/saccade ratio by input device.

Input Device and Age

There was a significant two-way interaction effects of input devices * age on mean saccade durations (F (1,198) = 10.470, p = .001). Older adults had higher mean saccade durations when they were in the condition of the touchscreen device (Figure 5).

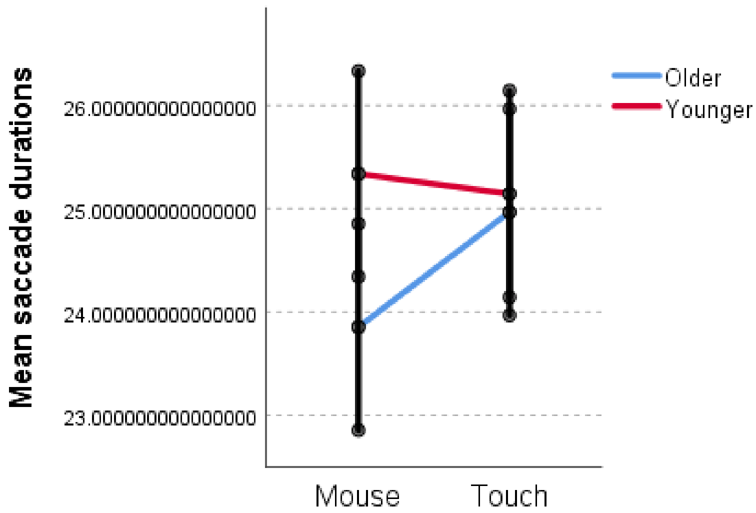

Figure 5. Mean saccade duration by age and input device.

There was a significant two-way interaction effect of input device * age on saccade amplitudes (F (1,198) = 11.470, p = .001). Older adults had higher saccade amplitudes when they were in the condition of the touchscreen device (Figure 6).

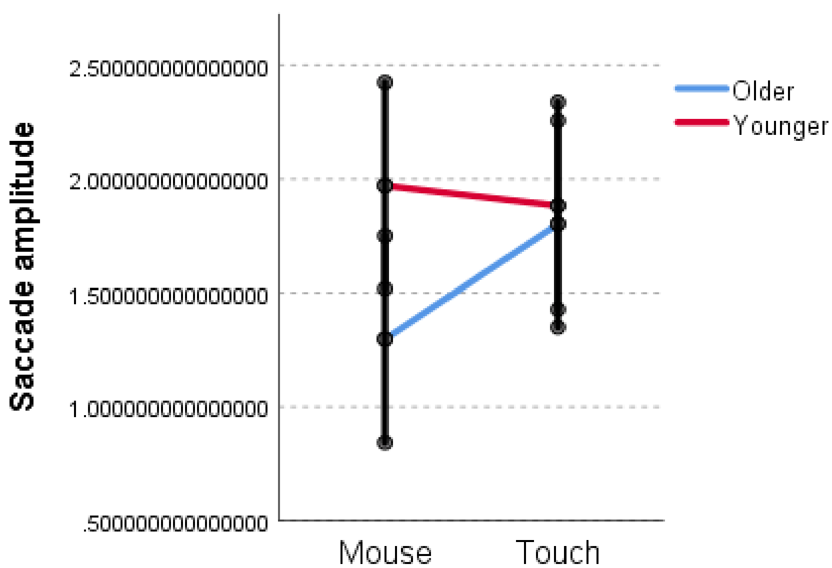

Figure 6. Saccade amplitude by age and input device.

Abnormality Variable Binary Classification

Consistent with our findings in our (in press) paper in *Human-Automation Interaction*, pupil size was significantly larger during the abnormal situations than the normal situations, indicating a higher cognitive workload during the abnormal situations. A binary logistic regression was applied to investigate if the Logit P(x) values could predict the abnormal events. The overall prediction accuracy was 75% for the low task load and 91.1% for the high task load. Moreover, in the low task load condition, the prediction accuracy was 76.7% for older adults and 69.7% for younger adults. In the high task load condition, the prediction accuracy was 91.6% for older adults and 94.3% for younger adults (Table 2).

Table 2. Prediction accuracy for older and younger adults.

Abnormal prediction	low task load	high task load
Older	76.7%	91.6%
Younger	69.7%	95.3%

4. Discussion

The analysis of eye-tracking measures gave us an indication of operators' attention, cognitive workload, and SA throughout the abnormal detection process at both the overall level and the prediction level. During the abnormal situation scenarios, participants alternated between two types of input devices, touchscreen and mouse. Our results showed that participants had lower mean fixation durations when they were in the condition of the touchscreen device. Fixation duration is a sensitive indicator of SA (Salehi et al. 2018), implying lower SA in the touchscreen device condition. Moreover, participants had lower fixation/saccade ratios when they were in the touchscreen device condition, which might be explained by their lower SA in the touchscreen condition resulting in more time spent searching for than processing information, which is consistent with the fixation duration results.

The two age groups, younger and older, were asked to do the same monitoring task. Older adults had higher mean saccade durations when they were in the touchscreen device condition. Thus, saccade duration indicated that participants experienced more cognitive processing with touchscreens (Das et al. 2018). Moreover, we found that older adults had higher saccade amplitudes when they were in the touchscreen device condition, indicating that older participants had lower cognitive workload with touchscreens (Li et al. 2018). Though older adults required more cognitive processes to finish the task, it was noticed that they maintained lower levels of cognitive workload in dealing with abnormal situations when using touchscreens.

With regard to model prediction, we found that the overall prediction accuracy of the mathematical model was 75% for the low task load and 91.1% for the high task load, which can be argued that this statistical model is generalizable to different task loads. Because the repetitive task operations in smart manufacturing impose more cognitive demands, there is a need to develop system models for measuring and predicting human performance (Bommer & Fendley, 2018). Given that participants' pupil size increased significantly in abnormal situations, indicating a higher cognitive load (Sharma et al. 2016), our model uses fixations and saccades to predict changes in cognitive workload. A person's accurate SA has a direct and positive influence on performance (Endsley 2019). Our model combines fixation durations, saccade durations, fixation/saccade ratios, saccade amplitude, and fixation numbers that reflect human workload, attention, and SA, which can accurately reflect whether the participant will have a positive performance in the next few seconds. The prediction accuracy is lower for the low task load than the high task load. One possible reason is that participants felt less workload in the low task load trials and therefore had smaller changes in eye behavior in abnormal situations.

We also applied the mathematical model to different age groups to investigate if it is generalizable to different populations. We found that with low task load, the prediction accuracies for older and younger adults were 76.7% and 69.7%, and with high task load, the prediction accuracies for older and younger adults were 91.6% and 94.3%. It can be argued that this mathematical model is generalizable to different populations such as older and younger adults.

Limitations and future research

We simplified the control room environment to focus on only abnormal detection behaviors of dynamic gauges in a controlled laboratory. Since the visual behavior measures collected were sensitive to various factors, the obtained results might be less applicable to prediction than those obtainable from a real environment. Future studies can replicate the experiment settings with operators in a naturalistic control room environment and to evaluate the robustness of the mathematical model.

Conclusion

This study tested a statistical model using visual behavior to predict human performance. Moreover, we examined the visual behavior of operators in abnormal situations in relation to age group, task load, task complexity, and input device. Our results showed that visual behaviors can indicate specific internal states of participants in different age groups and with different task loads. The findings demonstrate the value of using visual behavior in studies of oil refinery operators' performance and offered a new model to predict the hazards in today's smart manufacturing.

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