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# Physiological and Eye Tracking Determinants as Markers of Skill Acquisition in Manual Inspection

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## ABSTRACT

Skill acquisition in the manufacturing industry is a crucial aspect of optimising performance, efficiency, and safety in complex work environments. Human factors play a significant role in skill acquisition, encompassing factors such as cognitive processes, perception, decision-making, and physical interactions within the work environment. The aim of the current research is to understand the duration required to acquire skills through procedural learning and the transition to routine development occurs when leaned behaviour becomes habitual while faced with Mental and physical fatigue. Participants completed an inspection task that involved an industrial component (monitor) for their serial number, visual and tactile quality under a control condition: control (no manipulation) measuring physical demand and stress levels during each monitor inspection. Physiological measures were captured using a EmpaticaE4 wristband (capturing electrodermal activity (EDA), heart rate, skin temperature) and eye tracking was performed with Tobii Glasses 3, as well as subjective measures of performance via NASA TLX. The results from the physiological data show that the initial 10 minutes of the task showed a positive significant correlation between EDA and NASA Performance score, the second set of 10 minutes positively correlated EDA and NASA TLX temporal demands, while final 10 minutes showed a positive correlation between EDA and NASA TLX physical demand. Such results indicate that skill acquisition over time goes through several stages – individual's anxiety of their performance, then concerns for timely performance, and finally experiencing physical impact – as well as that EDA is good indicator of changing workload demands.

**Keywords:** Physiological data, Skill acquisition, Mental workload, Physical demand, Manufacturing, Fatigue

## INTRODUCTION

Skill acquisition within the manufacturing industry constitutes a pivotal aspect of operational efficacy and workforce performance. It encompasses the process through which individuals acquire proficiency (Nakamura et al., 2021) in executing tasks, operating machinery, and navigating complex production environments. However, this acquisition of expertise is not in isolation; it is profoundly intertwined with various human factors, operator well-being, stress management, and physical discomfort, all of which significantly influence the learning process and subsequent performance outcomes. Moreover, advancements in technology have ushered in novel methodologies for assessing skill acquisition, including eye tracking (Mark et al., 2020) and physiological measures such as heart rate and electrodermal activity (EDA). Understanding the intricate interplay between these multifaceted dimensions (Reiman et al., 2021) is essential for optimising training protocols, enhancing worker safety, and maximising productivity within the manufacturing sector.

In recent years, technological advancements have introduced novel methodologies for assessing skill acquisition within manufacturing environments. Eye tracking technology enables researchers to monitor visual attention (Hodges et al., 2021) and gaze patterns (Toker et al., 2014), providing insights into cognitive processes and task performance. Physiological measures such as heart rate and electrodermal activity (EDA) offer objective indicators of cognitive load, stress levels, and emotional arousal, thereby facilitating a deeper understanding of skill acquisition processes.

## MENTAL STRESS

Operator well-being is another critical aspect that directly impacts skill acquisition within manufacturing settings. The physical and mental health of workers significantly influences their ability to learn (Sgarbossa et al., 2020), adapt, and perform tasks effectively. Mental demand refers to the cognitive workload placed on an individual, often resulting in feelings of overwhelm and exhaustion. When coupled with high physical demands, such as long work hours or strenuous activity, stress levels can escalate, impacting both mental and physical well-being.

Performance may suffer as attention becomes divided, and errors increase due to cognitive overload. Effort increases as individuals strive to maintain optimal performance despite mounting stressors. Frustration levels rise when tasks exceed skill levels or when external factors impede progress (Sari et al., 2021). Excessive or chronic stress can impede skill acquisition, impair decision-making, and compromise worker safety (Omair et al., 2019). Therefore, effective stress management strategies are essential for optimising learning outcomes and promoting operator well-being. A study conducted on identifying factors of mental stress as mental demand, physical demand, temporal demand, performance, effort and frustration level (Hart & Staveland, 1988). These factors have helped mitigate the negative impact of stress on skill acquisition and performance.

## PHYSICAL DEMAND

Physical discomfort, stemming from factors such as repetitive motions, awkward postures, and prolonged standing, poses another significant challenge within manufacturing environments. These ergonomic stressors can contribute to physical fatigue (Yung et al., 2020), musculoskeletal (Márquez Gómez, 2020) disorders, and decreased productivity. Implementing ergonomic interventions such as adjustable workstations, mechanised assistance, and ergonomic training programs can alleviate physical discomfort and enhance skill acquisition.

## THE PRESENT PAPER

The current study addresses a cooker hood manufacturer, Silverline, within the AI PRISM project known as a use case. The use case consists of the cooker hood inspection whereby operators are required to ensure the appropriate quality of cooker hood. The current paper focus on the human factors analysis to provide the benchmark information for the skill development. Specifically, the mental and physical demand involved in the manufacturing industry which shapes and dictates worker wellbeing as well as the acquisition of skills through their development process during task completion. Furthermore, the research also explores performance in terms of response time and accuracy during an inspection task alongside physiological measures such as EDA and eye tracking data to explore how operators' skill development is determined. To achieve these aims the initial work conducted in this study will perform observations conducted as part of a controlled lab experiment and quantitative data collection based on the Silverline use case.

## METHODOLOGY

### Participants

The study involved twelve participants: all participants completed an inspection task on a computer monitor. Participants were aware that they were being observed, hence an overt observation took place. three females (Mean Age = 30.5) and nine males (Mean Age = 27.3).

### Ethics

This research was approved by the Cranfield University Research Ethics Committee, and conducted in accordance with the Cranfield Research Integrity Policy, the British Psychological Society's Code of Human Research Ethics, and the General Data Protection Regulation 2018.

### Materials

**PC Monitors:** Three monitors were used as part of equipment to simulate a conveyor belt motion. Participants were to assess the quality of the monitors within a simulated testing area. Monitors were connected to a power source as well as a laptop and mouse for participants to navigate through the quality control aspect.

**Eye tracking glasses:** Tobii Eye Tracking Glasses 3. The eye-tracking data was analysed using Tobii 3 eye-tracking analysis software, utilising the semantic gaze mapping focusing on the two Areas of Interest (AOI) and investigating the average duration of fixations in these areas as well as number of visits.

**Empatica E4:** A wristwatch type device (Empatica E4) measured heart rate and electrodermal skin activity (EDA). Heart rate is known to increase with decreased physical comfort/increased activity and decrease with increased engagement/trust (Edwards & Kelly, 2017), while EDA increase with increased discomfort and mental workload (Kosch et al., 2019).

### Self Report Data

**NASA TLX: The Mental Workload** was measured using the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988). It measures participants' experience of a task across six different dimensions such as physical, temporal and mental demand, effort, frustration and performance. For each, the participant rates their experience across a 21-point scale.

Additional self-report measures were collected, however not analysed in the current study- Nomophobia Questionnaire (NMPQ), Information Privacy Scale (IPS), Computer Aversion, Attitudes, and Familiarity Index (CAAFI), Ten item Personality Inventory (TIPI), Technology self-efficacy (TSE), Technology readiness (TR) as well as stress and physical discomfort scale.

**Stress and Physical Discomfort Scale:** Derived from the general labelled magnitude scale. The labelled magnitude scale (LMS) is a hybrid scaling technique using a verbally labelled line with quasi-logarithmic spacing between each label. The scale consists of a vertical line, which is marked with verbal anchors describing different intensities (e.g., "weak," "strong") (Jones et al., 2017).

### Procedure

Upon being briefed on the data collection aims, participants were guided through the informed consent and signed that they voluntarily agree to take part in the study. The NMPQ, IPS, CAAFI, TIPI, TSE and TR was completed prior to the inspection task. Participants were then assisted in putting on the eye tracking glasses, Empatica E4 wristband. The participants were then shown once how to complete the task with reference to an instructions sheet placed above the simulated testing area. The instructions were as follows:

1. Collects monitor A from **conveyor belt area** across to **testing area.**
2. Connect the **HDMI cable** to the monitors HDMI port.
3. Connect the **power cable** into the socket on the monitor, then connect the plug into the spare socket on the wall.
4. Switch **on** the socket at the wall.
5. Press the power button on the monitor to switch it on.
6. Once the monitor is on, using the mouse provided, head to Settings -> Display Settings -> **Advance Display Settings -> Properties -> Events**
7. Check the **DISPLAY** serial number against the check sheet.
8. Once serial number has been identified, press the **power button to switch the monitor off.**
9. Switch the **socket off** at the wall.
10. **Unplug** from the wall.
11. Disconnect the **power cable and HDMI cable.**
12. Perform quality Control: touch around the edges of the monitor to see if there are any identifiable scratches. If you detect any, please not it down in the list.
13. Place the monitor at **the end of the conveyor belt line** and begin the same process again with the next monitor(s).

The condition consisted of having a simulated conveyor belt area and a testing area for participants to navigate through the experiment. Participants lifted and collected one monitor at time from the conveyor belt to the testing area, they were then required to plug the monitor into the laptop so that it was functioning correctly as well as then connecting the HDMI cable to the laptop where they could then check the serial number and code of the specific monitor provided. Participants had to navigate through the serial number check by using the mouse provided and noting down the serial number on a predefined checklist. They then completed an inspection check around the monitor by looking out for any scratches using their hands by feeling for any tactile information and noting this onto the predefined checklist before disconnecting all cables. After each inspection check they were required to indicate their physical discomfort and stress level using scales provided. They then lifted the monitor and placed it back onto the conveyor belt. This process was then repeated for a total of 10 minutes, participants were then given instructions to complete the NASA TLX before returning to their session to complete an additional 10 minutes and this process was repeated overall 3 times.

## RESULTS

### Response Time and Accuracy

There was also an increase in the development of skill acquisition whereby by participants displayed a decrease in error count (from 1 to 0 over the inspection of 30 minutes), instruction analysis and increase in time of task completions as the average time reduced from 3 minutes 20 seconds ($SD = 0.08$) for the first component to 1 minute 48 seconds ($SD = 0.03$) for the last component. The Spearman's rho correlation indicated a strong negative effect ($rho = -0.794$, $p = 0.00$, $n = 10$). Taking together accuracy and response time, results indicate that as time goes by participants acquire the new skill and internalise the task instructions/acquire the manual skill needed for the task.

### Mental Workload

One of the main interests of the study were the changes in the mental workload through skill acquisition. The NASA TLX scores were repeated in the intervals of 10 minutes capturing the initial response, mid-process and late response to the task on six factors of Mental Demand, Temporal Demand, Physical Demand, Effort, Performance, and Frustration.

A 6 by 3 repeated measures ANOVA (6 factors of NASA TLX vs 3 time windows) showed the main effect of Factor to be significant ($F(5, 50) = 13.07$, $p < 0.001$, $\eta^2 = 0.566$). The main effect of time and the interaction Factor by Time were not significant ($p > 0.189$). Post hoc analysis of the main effect of Factor with Bonferroni correction indicated that Performance factors was higher evaluated than other factors ($p < 0.023$, Table X), however there were no other significant differences.

**Table 1.** NASA TLX factors means, standard errors, and p-value comparing performance factor with other factors.

| *Factor* | *Mean* | *Std. Error* | *Performance vc other factors p value* |
|---|---|---|---|
| **Mental Demand** | 3.152 | 0.574 | 0.002 |
| **Physical Demand** | 4.636 | 0.646 | 0.024 |
| **Temporal Demand** | 4 | 0.615 | 0.003 |
| **Performance** | 8.545 | 0.369 | |
| **Effort** | 3.939 | 0.572 | 0.003 |
| **Frustration** | 3.636 | 0.7 | 0.023 |

## Physiological Data

The second step of the analysis was concerning physiological markers of the skill acquisition. As the behavioural data indicated decreasing response time for completing the task (participants were quicker over time) the data was segmented into three sections: early task performance 0:00–10:00 minutes, mid performance 10:01–20:00 minutes and late performance 20:01–30:00 minutes. These three-time windows were used to compare the data with non-parametric Friedman repeated measures test to see whether there were differences in physiological data (EDA, HR, Skin Temperature) depending on the task duration. The only approaching significance result was observed with the heart rate ($\chi 2 = 5.17$, $p = 0.08$). further investigation with Wilcoxon Signed Rank test showed that participants heart rate was significantly lower during the first 10-minute window compared to the second 10-minute window ($Z = 2.20$, $p = 0.028$) and at a trend level lower than in the third time window ($Z = 1.65$, $p = 0.099$), however there was no significance between first- and third-time windows ($p = 0.470$).

To test whether and how the physiological data and self-report task load scores relate to each other, non-parametric Spearman's rho correlation was performed. The results from the physiological data show that the initial 10 minutes of the task showed a positive significant correlation between EDA and NASA TLX Effort score (Spearman rho = 0.675, $p = 0.016$), the second set of 10 minutes positively correlated EDA and NASA TLX Temporal Demands (Spearman rho = 0.757, $p = 0.004$), while final 10 minutes showed a positive correlation between EDA and NASA TLX Physical demand (Spearman rho = 0.639, $p = 0.025$) and Mental demand (Spearman's rho = 0.580, $p = 0.048$). Interestingly, neither heart rate, nor skin temperature ratings correlated with NASA TLX scores.

## Eye Tracking

Finally, to understand how participants are learning the new task, eye tracking gaze mapping and fixation duration analysis was performed with Tobii eye tracking glasses 3. Two areas of interest (AOI) were defined – the written instructions displayed in front of assembly area, and the monitors themselves. The analysis is undergoing; however, the preliminary results suggest that unsurprisingly participants had larger durations of fixations and number of visits to the monitor AOI compared to instruction AOI (Table 2). Interestingly, number of visits to instruction AOI was related to number of errors participants performed in the assembly. Further analysis will consider the changes in fixation duration during three-time windows as well as changes in fixation count and its relationship to the errors in the assembly.

**Table 2.** Eye tracking metrics as a FUNCTION of AOI and error count performed in the quality inspection.

| Participant | Total duration of fixations | | Number of Visits | | |
|---|---|---|---|---|---|
| | Monitor | Instructions | Monitor | Instructions | Errors |
| 1 | 236949 | 8595 | 989 | 45 | 2 |
| 2 | 258417 | 3216 | 1053 | 1 | 3 |
| 3 | 28882 | 1072 | 17 | 2 | 1 |
| 4 | 6792 | 0 | 9 | 0 | 1 |
| 5 | 26569 | 0 | 35 | 0 | 0 |
| 6 | 1803 | 0 | 9 | 0 | 2 |
| 8 | 60730 | 0 | 110 | 0 | 1 |
| 9 | 9397 | 0 | 20 | 0 | 1 |
| 10 | 7323 | 0 | 20 | 0 | 0 |
| 11 | 87768 | 11691 | 201 | 63 | 0 |
| 12 | 1513 | 0 | 7 | 0 | 0 |

## CONCLUSION

The exploration of skill acquisition as a dynamic process, characterised by distinct stages and influenced by various factors such as anxiety, timely performance concerns, physical impact, Electrodermal Activity (EDA), individual timings, and eye tracking, has provided valuable insights into the complexities of learning and performance.

The result indicates the process individuals undergo in acquiring new skills, from initial apprehension about performance displayed in EDA data to the challenges of meeting deadlines under new provided instructions and eventually experiencing physical strain, a comprehensive framework has emerged, offering an understanding of the underlying mechanisms driving skill development. For example, the results indicate that the time taken to complete the task significantly reduced over the course of the experiment indicating that through constant repetition of specific movements and tasks meant that the skill involving inspection was acquired. As response time decreases and accuracy improves, it reflects the refinement and consolidation of acquired skills through practice and learning. This reduction in response time and increase in accuracy underscore the progressive mastery and efficiency gained through experience and skill development.

Integrating physiological measures like EDA into the analysis has proven to be an effective method for monitoring changing workload demands throughout the skill acquisition process. By quantifying physiological responses to task demands, EDA relates to performance, physical and mental demand, allowing for different workload factors through the time, however, more extensive data is needed to draw conclusion and establish whether monitoring of EDA can reliably inform about individuals experienced task loads. For example, sourcing the original workload factor that leads to increased EDA such as mental stress or performance demands. This supports the following research that stress and performance are factors influencing the mental workload placed on workers the impact the development of skills (Omair et al., 2019). For example, the study found that average stress among workers on the production system was individualised through their individual experience through intensity and level of stress.

Furthermore, incorporating individual timings and eye tracking data enhances the granularity of analysis, providing insights into the visual attention patterns associated with skill acquisition. The eye tracking data revealed. The eye tracking data revealed that participants had significantly longer durations of fixations and made more visits to the monitor AOI than the instruction AOI. Intriguingly, a correlation emerged between the frequency of visits to the instruction AOI, and the number of errors participants made during the assembly task, suggesting a potential link between attentional focus and task performance. These findings underscore the importance of understanding visual attention allocation in complex tasks and its implications for error prevention. Thus, supporting previous evidence by reaffirming the significance of visual attention allocation in complex tasks (Toker et al., 2014), particularly in relation to error prevention. The longer durations of fixations and increased visits to the monitor AOI compared to the instruction AOI align with prior research indicating the importance of certain visual cues or stimuli over others in task performance.

Firstly, the generalisability of findings may be limited by factors such as sample size, participant characteristics, and task specificity. Additionally, the reliance on objective measures like EDA and eye tracking may overlook the subjective experiences and individual differences that influence skill acquisition processes (Valtakari et al., 2021). To build on this work and address these limitations, future research should adopt a multi-method approach that integrates quantitative and qualitative measures to capture the full complexity of skill acquisition. Longitudinal studies tracking individuals over extended periods could elucidate the trajectory of skill development and identify critical factors that facilitate or hinder progress. Furthermore, exploring the role of contextual factors such as learning environments and social support networks could provide valuable in terms of insights into the time in which operators effectively (Sgarbossa et al., 2020) complete their tasks, EDA and the eye tracking data. Ultimately, by embracing interdisciplinary approaches and leveraging emerging technologies, we can continue to advance our understanding of skill acquisition and enhance our ability to support individuals in their journey towards skill mastery.

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