Pupil Responses as Indicators of Learning and Adaptation in Human-Robot Collaboration Scenarios

Davide Zanardi
davide.zanardi.1@phd.unipd.it
Department of Developmental Psychology and Socialization
University of Padova
Padova, Italy

Federica Nenna
federica.nenna@unipd.it
Department of General Psychology
University of Padova
Padova, Italy

Egle Maria Orlando
eglemaria.orlando@phd.unipd.it
Department of General Psychology
University of Padova
Padova, Italy

Margherita Nannetti
margherita.nannetti@studenti.unipd.it
Department of General Psychology
University of Padova
Padova, Italy

Michele Mingardi
michele.mingardi@unipd.it
Human Inspired Technology Research Centre University of Padova
Padova, Italy

Giulia Buodo
giulia.buodo@unipd.it
Department of General Psychology
University of Padova
Padova, Italy

Luciano Gamberini
luciano.gamberini@unipd.it
Department of General Psychology
University of Padova
Padova, Italy

ABSTRACT

The shift towards a more human-centric manufacturing approach in Industry 5.0 emphasizes the integration of technologies that augment rather than replace human capabilities, highlighting the role of collaborative robots (cobots). These cobots, designed to work closely with human operators, bring adaptability and efficiency to the manufacturing floor, adjusting to various tasks and production needs. This integration, while promising, introduces challenges, especially in terms of human adaptation and learning in dynamic work settings. To date, research has primarily focused on the technological advancement of cobots, often overlooking the human component in this collaborative equation. Our study seeks to bridge this gap by employing pupillometry to explore learning effects within human-robot collaboration (HRC), specifically examining human adaptation to complex and extended tasks reflective of industrial environments. Through a multifactorial design involving 19 participants engaged in three trials repeated for two task difficulty levels, the research analyzes performance metrics along with changes in pupil diameter. The results discovered that repetitive task execution is related to decreased operation time and pupil diameter, suggesting reduced cognitive load levels. These findings imply the potential utility of pupillometry as an indicator of human adaptation to complex task execution, promoting further investigation into physiological measures to optimize cobot integration into the workplace.

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CCS CONCEPTS

• **General and reference** → **Measurement**; • **Applied computing** → *Industry and manufacturing*.

KEYWORDS

Eye-tracking, Industry 5.0, Collaborative Cobots, Task learning

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1 INTRODUCTION

Industry 5.0 advanced a transition from a techno-centric to a human-centric approach, positioning the well-being of workers at the forefront of the manufacturing process. This change underscores the importance of creating a harmonious work environment where technology improves human abilities, rather than overshadowing them, ensuring that production methods are effective and support worker welfare [10], [24]. In this context, collaborative robots, or 'cobots', equipped with advanced sensors and a variety of capabilities are becoming a focal point of research due to their ability to work alongside and support human workers in their tasks, allowing smooth and efficient collaboration [7].

One of the main features of cobots is their remarkable flexibility in adapting to new tasks. They can be easily programmed and reconfigured, facilitating smooth transitions between different production cycles and dynamically adapting production lines to new requirements[6]. This capability is particularly valuable in the context of the modern industry, where product customization and the need to respond to constantly changing and fast-paced demands have increased significantly [19].

The flexibility of cobots mirrors that of human capabilities [2]. This similarity facilitates effective collaboration, allowing human-cobot teams to adapt efficiently to diverse scenarios. In such teams, cobots are typically assigned repetitive or physically strenuous tasks, which complements the human role focused on decision-making, creativity, and tasks that require manual dexterity [4]. However, it is important to consider that while cobot integration can reduce the physical demands placed on workers, it could also lead to increased mental fatigue and stress due to the complexities of managing a more dynamic work environment [17]. The flexibility of human-cobot teams allows frequent modifications to production line workflows [9]. Consequently, human operators are required to adapt to new procedures regularly. Although this adaptability is fundamental to improving industrial efficiency, it also raises questions about human adaptation capacity and the flexibility to keep pace with such frequent changes. Critical considerations arise about the duration required for adaptation and the cognitive load these changes impose on human operators. The majority of existing research predominantly emphasizes learning from the robot's perspective, frequently neglecting the human component. As such, further investigations are needed to bridge this gap by investigating human adaptation and learning processes in collaborative work settings.

1.1 Pupil diameter variations in response to task learning and adaptation

The pupil diameter has been extensively investigated within the evaluation of cognitive load, vigilance, and stress detection, establishing itself as a sensitive and non-invasive physiological marker for changes in an individual's mental state [26], [14], [1], [14], [16]. Traditionally, variations in pupil diameter have been closely associated with cognitive load intensity and stress levels. Specifically, an enlargement in pupil diameter typically indicates a higher level of mental effort, signifying an increase in cognitive demand. On the contrary, a decrease in diameter is often interpreted as a decrease in cognitive load [8].

Recently, researchers have begun to investigate pupillometry to deduce learning processes. This approach suggests that as an operation becomes more automated, the cognitive load necessary for its execution decreases[20]. Therefore, this phenomenon would lead to a reduction in pupil diameter. This relationship provides a new window into the dynamics of task learning, allowing observations of how cognitive efficiency evolves with practice. Several studies have investigated how learning affects pupil diameter. White et al. [23] conducted an experiment in which participants controlled the movement of a cursor within a target, faced various task difficulties, and engaged in real and imagined movements. Their results showed an initial increase in pupil diameter under more challenging conditions, which decreased with time, suggesting that pupil size can dynamically reflect motor learning and adaptability to task complexity. Similarly, [21] assessed participants' ability to identify cardinal directions in a spatial orientation task, recording accuracy, reaction time, and pupil size. The findings indicated that learning improved performance in terms of better accuracy and faster reaction times, and the decrease in pupil size further contributed to validating pupillometry as a learning measure. Yokoi and Weiler's work [25], in a motor task involving a robotic device and an unfamiliar force field, demonstrated that pupil dilation responds to environmental novelty, increases under unfamiliar conditions, and decreases as tasks become more familiar.

Collectively, these studies indicate that pupillometry could serve as a reliable indicator of learning in various contexts. Yet, most of this research has been carried out in conventional laboratory environments. Whether the pupil diameter decreases with increased familiarity during task execution in more realistic and dynamic settings, such as those involving human-cobot interaction, remains to be investigated. Additionally, the tasks in these studies typically lasted only a few seconds. For the application of pupillometry in practical, real-world scenarios, it is also necessary to assess whether reductions in pupil size occur over longer periods.

1.2 Our Study

Building on this foundation, our research is dedicated to employing pupillometry to discern learning effects within the context of HRC. Our focus is on investigating the adaptability of this method to tasks characterized by extended duration, increased complexity, and a high degree of realism that mirrors the conditions found in industrial settings [15]. In doing so, we provide insight into the dynamics of HRC in time, exploring whether and how users assimilate new procedures and adapt to evolving task demands in the workplace. We have two major research questions:

Q1 Assess whether there is a learning effect when repeating multiple trials of the same assembly task with a cobot under two difficulty levels. In this respect, we hypothesize performance improvements over task repetitions.

Q2 Evaluate whether, within the same task, eventual performance improvements and human adaptation correspond to a decrease in pupil diameter levels.

To answer these questions, we implemented a 2x3 multifactorial design, where the Task demand varies across two levels of difficulty through dual-task manipulation, and the Trial condition is defined by the three repetitions each participant performed for these tasks. An experimental task with high realism and complexity was designed to mirror the cognitive demands of real-world work scenarios. By analyzing task performance metrics, such as error counts and operation time, along with physiological measures such as changes in pupil diameter across trials, we aim to investigate the effects of learning and adaptation across different task difficulties and repetition levels.

2 METHODS

2.1 Sample

We enrolled 17 participants in our study, including 9 women and 8 men, with an average age of 26.82 years (SD = 1.98). These participants, primarily university students, were non-experts using the cobot and volunteered for the study, providing informed consent. We selected participants based on criteria that excluded those with visual impairment or a history of neurological or psychiatric conditions. However, due to technical issues with eye-tracking data, we had to discard the records of two participants. The local ethics committee approved our experimental protocol (protocol number 2023_212). Our research is in accordance with the ethical standards outlined in the Declaration of Helsinki.

2.2 Technical setup

The experiment was conducted in a university laboratory, where the cobot and workstation were installed. The room was located away from external noise sources and was designed to maintain consistent lighting levels throughout the duration of the data collection. During the experimental session, participants wore eye-tracking glasses, specifically the Pupil Core model from Pupil Labs, with a sampling frequency of 30 Hz and an accuracy of up to 0.5 degrees of visual angle. Eye tracking data was collected using Pupil Capture software (version 3.5.1), operating on a DELL PC (model XPS 2720 equipped with an Intel Core i7-4790S processor and 16 GB of RAM), to which the eye tracker was connected via a USB cable. Two VHD-V61CL FullHD ambient cameras captured video recordings of the task with the footage analyzed using BORIS software (version 8.20.4). The experiment involved interaction with a collaborative robot arm UR10e, which has 6 degrees of freedom and can handle up to 12.5 kg, positioned at an adjustable height assembly workstation. The robot was controlled with Polyscope software (version 5.11). The workspace was equipped with an assortment of components such as screws, bolts, masks in black and transparent variants, and metal puzzle pieces of different shapes and colors, along with four metal plates, all placed in five boxes on the workstation. Data processing and analysis were performed using RStudio [18].

2.3 Experimental task and procedure

In the collaborative assembly task, we combined manual operations designed to reflect real-world manufacturing processes using the same procedure presented in [15]. This integration resulted in a workflow within a single trial that encompassed three primary operations: manual screwing, where participants worked alongside the cobot to position and secure a green plate; composition tasks involving the assembly of metal pieces into a specified configuration with the aid of the cobot; and supported screwing, where the cobot facilitated the final assembly and securing of a red plate using an electric screwdriver. The key moments of these operations are better explained in our previous work [15] and also depicted in Figure 1.

The experiment lasted approximately 90 minutes, beginning with an initial training session in which participants practiced one trial to familiarize themselves with the cobot and the specific task rules. To standardize information presentation, all instructions were provided textually on slides displayed on a monitor near the working area. This step also helps minimize the likelihood that participants will require assistance from the experimenters during task recordings. After the training, the participants confirmed their understanding before proceeding to the main experimental session. Each participant wore an eye tracker and the experimenter performed instrument calibration. The beginning of each trial included a 2-minute baseline period to measure baseline conditions for pupil diameter, and allowed the experimenter to rearrange the setup for the subsequent trial.

Figure 1: Participant engaged in accomplishing the three main operations of the experimental task.

The experimental design consisted of three single-task trials followed by three dual-task trials, with instructions provided via text and figures on a touchscreen desktop. In single-task trials, participants focused exclusively on the assembly task. Dual-task tests required participants to participate in the assembly task while continuously performing mental subtractions, specifically subtracting 3 from 1022, with any mistakes necessitating a restart from 1022. Participants were allowed breaks between the single- and dual-task segments, after which the eye tracker was re-calibrated.

2.4 Measurement and Statistical Analysis

In this study, we examined the average pupil diameter per trial. The data were processed by first removing unrealistic values and artifacts from the pupil size data [12]. We used the R pupillometry package [5] to average the values of the two eyes into a single value for each observation; we downsampled the data from 30Hz to 20Hz [13] to facilitate the subsequent analysis given the length of our recordings; we interpolated blinks and applied median filtering. Subsequently, we performed a subtractive baseline correction of a 200-ms window for each trial [12]. In the final step, we calculated the mean pupil diameter for each trial under different task conditions.

As performance metrics, we used the mean operation time and error rate. These metrics were derived from the analysis of video recordings of participants engaged in the task. In particular, the operation time was measured by specifically considering the duration of human actions related to completing the assembly task. Errors were defined as any instance where assembly objects were misplaced or omitted, pieces fell, or the assembly sequence was not respected.

For our data analysis, we employed Generalized Linear Models (GLMs) through the lme4 package in RStudio. The selection of the most suitable model for each metric was obtained using the descdist() function of the fitdistrplus package [3]. The analysis model for pupil diameter and performance metrics, including operation time and error rate, incorporated the factors of Task (i.e., single task and dual task) and Trial (i.e., Trial 1, Trial 2, Trial 3). We consistently treated the participant variable as a random effect in all analyses. Additionally, for the interpretation of post hoc contrasts within significant interactions, we implemented the Bonferroni correction to adjust for multiple comparisons.

3 RESULTS

The following sections present the model results. Descriptive statistics are reported in 1.

3.1 Performance

In the analysis of the effect of Task and Trial variables on operation time, a significant main effect was observed for Trial ($X^2 = 11.71$, $p < .01$). No significant effect was found instead for Task ($X^2 = .50$, $p = .48$), nor for the interaction between Task and Trial ($X^2 = 1.60$, $p = .45$). Post hoc contrasts on the Trial variable revealed significant differences between *Trial 1* and Trial 2 ($p < .05$), and between *Trial 1* and *Trial 3* ($p < .01$), but not between *Trial 2* and *Trial 3* ($p = 1$). Moreover, the analysis of the error rate did not show any significant results for Task ($X^2 = .63$, $p = .43$), Trial ($X^2 = 1.81$, $p = .41$), and their interaction ($X^2 = .17$, $p = .92$). Figure 2 depicts the performance results.

Table 1: Descriptive statistics for baseline-corrected pupillometry, error counts, and operation time by Trial and Task Condition.

	Pupillometry (*mm*)	
	ST	**DT**
	mean (SD)	*mean (SD)*
Trial 1	0.479 (0.541)	0.699 (0.758)
Trial 2	0.340 (0.571)	0.433 (0.470)
Trial 3	0.183 (0.545)	0.415 (0.500)
	Errors count	
Trial 1	4.25 (3.49)	2.62 (2)
Trial 2	3.44 (4.15)	2.31 (1.96)
Trial 3	2.19 (2.07)	2.31 (2.06)
	Operation time (*s*)	
Trial 1	224 (41.1)	219 (46.9)
Trial 2	196 (29.1)	206 (29)
Trial 3	193 (23.2)	202 (28.8)

3.2 Pupil diameter

In our analysis of the impact of Task and Trial on pupil diameter, we observed significant main effects for both Task ($x^2 = 330.26$, $p < .0001$) and Trial ($x^2 = 21327.40$, $p < .0001$). Furthermore, a significant interaction effect was detected between Task and Trial ($x^2 = 7919.95$, $p < .0001$).

Subsequent post hoc contrasts for the Task variable revealed a significant difference between the single- and dual-task conditions ($p < .0001$). Similarly, the contrasts for the Trial variable indicated significant differences across all Trail conditions: between *Trial 1* and *Trial 2* ($p < .0001$), *Trial 1* and *Trial 3* ($p < .0001$), and *Trial 2* and *Trial 3* ($p < .0001$).

The post hoc contrasts between the interactions of Trial and Task were found to be significant. For single-task conditions, significant differences were identified between *Trial 1* and *Trial 2* ($p < .0001$), *Trial 1* and *Trial 3* ($p < .0001$), and *Trial 2* and *Trial 3* ($p < .0001$). Similarly, in the dual-task conditions, significant differences were observed between *Trial 1* and *Trial 2* ($p < .001$), *Trial 1* and *Trial 3*

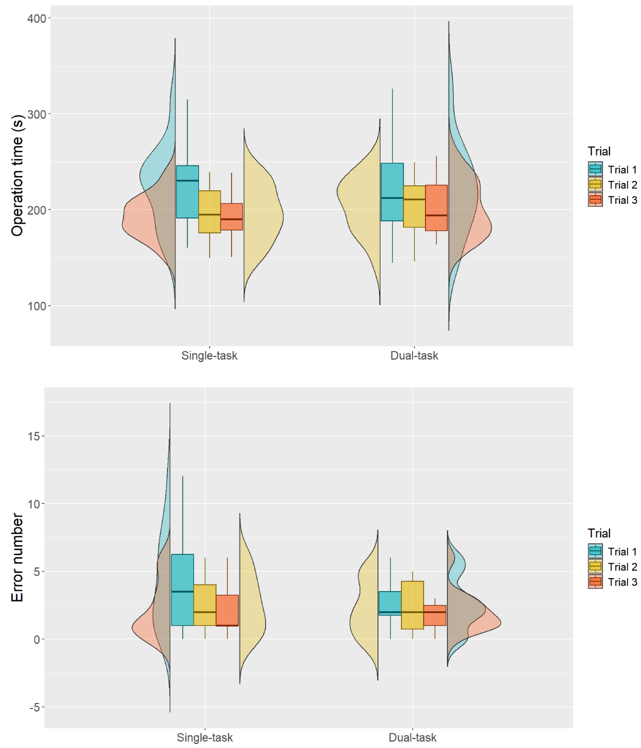

Figure 2: Average operation time (upper panel) and error number (lower panel) across trials for each task condition. Data distribution is represented using boxplot and half-violin plot.

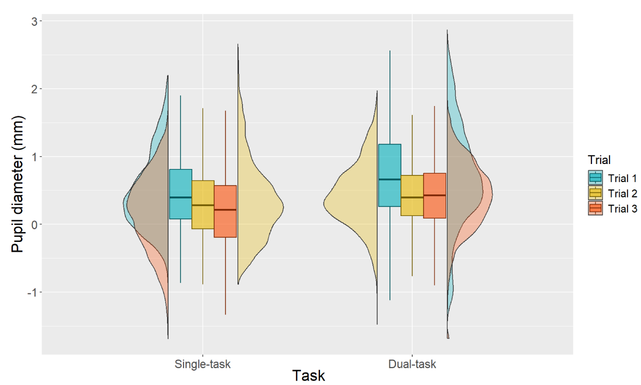

Figure 3: Baseline-corrected average pupil diameter across trials for each task condition. Data distribution is represented using boxplot and half-violin plot.

($p < .0001$), and *Trial 2* and *Trial 3* ($p < .001$). In Figure 3 the pupil dimension results are shown.

4 DISCUSSION

In this study, we addressed two research questions. The first was to verify the occurrence of task learning in a realistic assembly task performed in collaboration with a cobot, using performance metrics as indicators. The second assessed whether this ad aptation could also be detected by variations in pupil diameter. To achieve this, we engaged participants in collaborative assembly tasks designed to replicate the complexity and realism of industrial environments, thereby seeking to establish a link between theoretical insights and practical applications.

Answering our first research question, in terms of performance findings, the results partially align with our hypothesis. We observed a consistent trend of reduced operation time across all tasks, suggesting an improvement in participants' efficiency regardless of the task difficulty. This trend, evident in the mean operation time, suggests that participants began to learn and become more proficient in the execution of the trial. Furthermore, this trend was observed independently of the difficulty levels of the task (single task, dual task). On the contrary, when examining error rates, although there were variations in mean errors between trials, these differences did not reach statistical significance. This indicates that the increase in repetitions did not consistently lead to a reduction in error rate during task execution. Interestingly, our analysis did not reveal any performance degradation when comparing single- and dual-task conditions. This outcome was particularly surprising given the increased complexity of dual-task conditions. Since participants first experienced the single-task before proceeding to the dual-task condition in our experiment, the lack of notable differences in performance between these conditions may be due to a learning effect. This phenomenon could have enabled participants to maintain uniform levels of performance regardless of the complexity of the task. Overall, these results suggest the possibility that human learning during interaction with a cobot is effectively supported, potentially enabling human operators to swiftly adapt to new tasks and various levels of difficulty. However, studies that assess learning and adaptability in humans involved in HRC are scarce [22]. This lack of similar research within the HRC framework restricts our ability to compare these findings with existing studies.

In addressing our second research question, we observed a consistent decrease in pupil diameter across the three trials. This pattern could signal a reduced cognitive load through repetition, suggesting that participants are becoming more adapted to tasks [20]. When interpreting this result about the pupil diameter decrement along with the decrease in operation time, a similar trend is observable across metrics. In both cases, an increase in the number of trial repetitions is associated with an improvement in the operation time (i.e. from trial 1 to trial 2 and trial 3) and a consistent reduction in pupil diameter, possibly indicating a decrease in cognitive load. These results together support the idea that the pupil diameter seems to reflect task learning. This finding is also consistent with other studies that have observed similar effects in different contexts [23], [21], [25]. Interestingly, the learning effect evidenced by changes in pupil diameter does not seem to be influenced by task complexity. Specifically, we observed a general decrease in pupil diameter during single-task repetitions, followed by an initial increase when participants switched to dual-task activities. This increase, which may reflect the increased cognitive demand associated with dual-task conditions compared to single-task phases, confirms the efficacy of our experimental manipulation. Furthermore, this observation may indicate that the learning effect can be evaluated even under a high cognitive demand condition where additional cognitive processes (e.g., arithmetic tasks) contribute to modulating the pupil diameter [11].

5 CONCLUSION

Taken together, these observations imply that pupil diameter might be a reliable indicator for evaluating how individuals adapt to tasks of different complexity, which encourages further research into this physiological measure in adaptive work environments. Furthermore, the observed patterns of pupil diameter variations when transitioning from the single-task to the dual-task represent promising results, indicating a potential for operators' capability to swiftly transition from a simpler to a more complex task and adapt to it over a small number of iterations (i.e., three). This adaptability is particularly noteworthy in industrial contexts, where the flexibility afforded by human-cobot collaboration likely leads to frequent modifications of tasks and workflows.

Despite the promising findings, we must acknowledge certain limitations in our research. First, due to the substantial time required for subjects to complete a single assembly, the number of trials each participant underwent per condition is limited compared to studies exploring this phenomenon in other contexts [23], [21], [25]. Future research should extend the number of trials to improve understanding of how the pupillometry trend develops and stabilizes in relation to task learning and adaptation. Second, our study's sample was relatively small and consisted primarily of students rather than experienced cobot operators. Additional research is essential to examine the learning effects within an appropriately sized sample of operators to determine the influence of expertise on this phenomenon and to improve the ecological validity of the findings. Third, the study did not incorporate self-report measures along with physiological and behavioral metrics, which could provide additional information learning effects. Future studies should address these limitations and explore the extension of the use of pupil diameter as a task-learning indicator to improve cobot adaptability algorithms and broaden the applicability of this measurement.

In general, pupil dilation appears to be a promising metric for assessing trial learning in the HRC context. Further studies are yet essential to comprehensively explore this dimension, shedding light on aspects of both robot and human learning as well as task adaptation. Such research could facilitate a shift toward a more rapid and dynamic work environment by developing solutions like training evaluation, work pace optimization, and cobot behavior adjustments that consider the human learning and adaptation process.

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