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Eye-tracking support for analyzing human factors in human-robot collaboration during repetitive long-duration assembly processes

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Abstract
The integration of eye-tracking technology in manufacturing is emerging as a powerful tool for optimizing human performance and well-being in the workplace. Advances in various fields enabled the recent development of smaller, wearable, and wireless eye-tracking devices which are suitable for naturalistically studying manufacturing processes, such as human-robot collaboration (HRC). However, the implementation of eye-tracking for evaluating mental workload in HRC is still limited, especially in long-duration sessions. This paper provides an overview on the application of eye-tracking technology in the context of cognitive ergonomics within the manufacturing sector, with special attention to eye-tracking metrics and their interpretation relatively to human state in long-duration sessions (i.e., work shifts). In addition, an example case study will be presented to explore the reliability of the most common eye-tracking metrics, concerning a repetitive assembly process of 8 h in an HRC setting. Among the explored eye-tracking metrics, pupil dilation, number and average duration of fixations, and number saccades provided useful insights on the mental strain in dynamic conditions. In addition, from the multiple information gathered by eye-tracking, different phenomena related to mental workload were able to be distinguished. The use of cognitive resources resulting from learning process was well detected by pupil dilation, number of fixations and saccades. Mental fatigue, on the other hand, was well detected by the average duration of fixations and the pupil diameter. These results highlight the need to consider multiple eye-tracking metrics simultaneously to obtain a holistic view of the operator's psychophysiological state.

Keywords Eye-tracking · Human-robot collaboration · Industry 5.0 · Cognitive ergonomics · Mental stress · Mental strain

1 Introduction

Eye-tracking is a measurement process of eye movements to understand where a person is looking, what they are paying attention to, and how their eyes move as they observe a scene or interact with a particular object or environment [1]. This technology typically utilizes specialized hardware, such as eye-tracking devices or cameras, to track the position of the eyes and record the data [2]. In the early stages, eye-tracking systems were large and cumbersome, often requiring elaborate setups and specialized laboratories. However, thanks to advances in fields such as optics, electronics, and computer science, the evolution of eye-tracking technology has enabled the recent development of smaller, wearable, and wireless eye-tracking devices. Such devices thus allow eye-tracking technology to be implemented outside the laboratory, paving the way for new application opportunities in the manufacturing context.

Eye-tracking is a valuable tool for understanding how individuals visually interact with their environment [3]. It has been used in diverse domains, including market research, neuroscience, user experience design, gaming, healthcare, and human factors engineering [4]. Ongoing research and

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innovations promise further developments, making eye-tracking an increasingly versatile tool for understanding human behavior and optimizing human-machine interactions [5].

The eye-tracking metrics provide a unique window into the cognitive processes engaged by workers during manufacturing tasks. By monitoring eye movements, fixation durations, saccadic patterns, and other metrics, it is possible to gain a deeper understanding of aspects related to mental workload experienced by workers. In the context of Industry 5.0, it becomes increasingly important to understand how new technological paradigms, such as human-robot collaboration (HRC), can impact and cognitively support the operator. The wearability of the eye-tracker and the non-invasive acquisition of eye data are particularly relevant for studying HRC in a naturalistic manner, as well as improving overall human performance and well-being [6]. HRC is an interaction paradigm aimed at combining the skills of collaborative robots (also called cobots) with those of human operators to achieve a common goal [7]. To achieve full and true collaboration, it is crucial to consider aspects related to user experience, which also include usability. Over the years, various works have explored various methods and interfaces to enable the human operator to interact naturally with a robot [8]. In this context, eye-tracking has often been successfully implemented in communication interfaces for various purpose [9]: for example, to allow the user to point to an object of interest with his or her gaze, guide the robot to a location, and let the robot know where the user's attention is placed [10]. Eye-tracking technology is often implemented in virtual reality (VR) or augmented reality (AR) devices through which gaze-based human-robot interaction can be established [11]. However, eye-tracking can also be used to obtain information on aspects related to the mental workload, such as the operator's mental state and cognitive processes. Emphasis on human factors proves to be crucial in order to fully exploit the benefits of HRC [12], especially from the human perspective [13]. In-depth exploration of such aspects requires refinement of eye-tracking technology to obtain richer information about eye behavior, including saccades and pupillary dilation. Such level of technology is not present in current commercial AR or VR devices, but only in specific eye-tracking devices designed to primarily perform measurements on eye behavior (e.g., Tobii Pro Glasses 3). Given the non-invasiveness of eye-tracking, it represents a valid solution for acquiring information related to cognitive ergonomics even during long-duration processes. However, in the literature, the use of such technology to study long-duration HRC manufacturing processes is rather limited.

The objective of this paper is therefore to show the potential of eye-tracking in assessing cognitive ergonomics in long-duration sessions (e.g., work shifts), while also providing an overview of the technology. In addition, an example case study will show (i) what are the advantages of implementing eye-tracking in entire work-shifts in HRC modality for detecting different phenomena related to mental strain and (ii) the concordance between different eye-tracking metrics for assessing the internal state of the operator.

The paper is structured as follows. Section 2 provides an overview of the literature concerning eye-tracking, its metrics and their interpretation in the context of cognitive ergonomics, and the applications of eye-tracking in manufacturing. Section 3 illustrates an example case study in which eye-tracking is used in a dynamic HRC context, showing the results of different eye-tracking metrics for evaluating mental workload during shifts. Discussion of the potential, benefits, and prospects of implementing eye-tracking technology in manufacturing is presented in Sect. 4. Finally, conclusions and future work are discussed in Sect. 5.

2 Literature review

In this section an overview of eye-tracking technology is provided, presenting the principles of eye movement, major eye-tracking methodologies, eye-tracking metrics, and the relationship to cognitive aspects. In addition, a literature review on the use of eye-tracking in the manufacturing context is also presented.

2.1 The eye and its movements

The eye is one of the most important sensory organs responsible for vision in humans and many other animals. It plays a vital role in the perception of the world, allowing for the interpretation of visual information in the environment [1]. . The human eye consists of several parts, including the cornea, iris, pupil, lens, retina, and optic nerve, all of which work together to capture and transmit visual information to the brain for processing (Fig. 1).

Eye movements refer to the motion and adjustments that eyes make as they scan, focus on, or track objects in the field of vision [1]. These movements are essential for processing visual information, maintaining clear and stable images, and directing attention to different parts of a scene or text. Eye movements can be classified into the following main categories:

- *Fixations*: they are periods of stable gaze during which the eyes remain relatively still, holding the foveal area (i.e., the sharp central vision area) in one place. Fixations

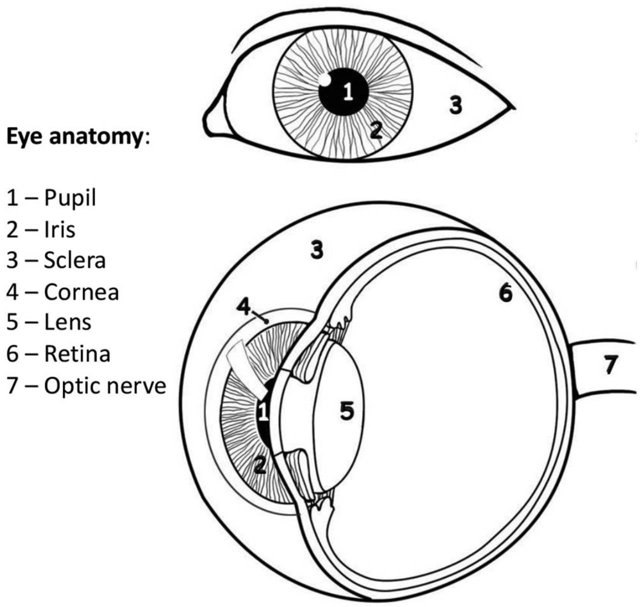


Fig. 1 Schematic anatomy of the eye

are important for gathering detailed visual information from a specific area of interest.

- *Saccades*: they are rapid, ballistic eye movements that rapidly shift the gaze from one point of interest to another. They are the quickest eye movements and are essential for scanning the visual environment.
- *Vergence movements*: they involve the slow movement in opposite directions of the left and right eye and are used to focus on objects at different distances. Far-to-near focus triggers convergent movements, while near-to-far focus triggers divergent movements.
- *Smooth pursuits*: they are an eye movement used to keep the foveal area aligned with moving objects, allowing to keep gathering visual information.
- *Vestibular ocular reflex*: it is an eye movement occurring when the head or body are moving. It involves the eyes moving in the opposite direction of the head to keep the foveal area at a point of interest.

The study of eye movements allows to gain insights into how individuals perceive and interact with their surroundings and to investigate various aspects of cognition and user experience. Fixations and saccades are the eye movements most commonly analyzed to gain insights into aspects related to cognitive ergonomics and user experience.

2.2 Eye-tracking methodologies

The development of eye-tracking technology has undergone significant advancements over the years and three main categories of eye movement measurement methodologies have established [1]:

- *Electro-oculography (EOG)*: This method measures the electrical potential difference between the front and back of the eyeball. Electrodes are placed around the eyes to detect changes in voltage caused by eye movements. EOG is robust and can work well even with closed eyelids, making it suitable for certain applications, such as sleep studies.
- *Scleral search coil*: This invasive method involves implanting a tiny coil in the eye, typically on the sclera and consists in external magnetic fields tracking the coils' position as the eye moves. The scleral search coil method historically established as the "gold standard" for very accurate measurements of eye movements, however, due to its invasiveness, this method is primarily used in scientific research and specialized medical studies.
- *Video-oculography (VOG)*: This method uses non-contact optical methods for measuring eye movement, e.g., cameras. Specialized algorithms analyze video data to track distinguishable features of the eyes, such as the pupil and its shape, the position of the limbus (i.e., the iris-sclera boundary), and corneal reflections of a close light source (e.g., infrared (IR)). Video-based eye trackers are the most popular variant, and typically use the corneal reflection and the center of the pupil as features to track over time. The advantage of video-based eye tracking over other methods is that it is relatively non-invasive, fairly accurate, and inexpensive.

In recent years, VOG has become the most commonly used eye-tracking method and the most commercially available eye-trackers are video-based ones (Fig. 2). This kind of eye-trackers can be distinguished in three main categories:

- *Head-stabilized eye-trackers*, which are eye-tracking systems typically used in neurophysiology that implement a method for constraining participant's head movements, such as a bite-bar or chin rest. This setup is primarily used in visual experiments where it is important to obtain extremely accurate data or where other biosensors that are particularly sensitive to movement are also implemented (e.g., functional magnetic resonance imaging (fMRI)). The main disadvantage of head-stabilized eye-tracking systems is the reduction in participant's comfort and naturalness of interaction.
- *Remote/Screen-based eye-trackers*, which are typically stationary devices that are mounted on or near a computer screen or display. They are designed for use in controlled environments, such as research labs or usability testing facilities, and allow a more natural visual

(a) (b)

Fig. 2 Examples of VOG eye-trackers: (**a**) the screen-based Tobii Pro Fusion and (**b**) the wearable Tobii Pro Glasses 3 [14]

Table 1 Summary of eye-tracking methodologies and their characteristics

Eye-tracking method	Setup	Measurable features		Invasiveness	Working area
		Eye movements	*Pupil behavior*		
Electro-oculography (EOG)	-	Yes	No	Medium	Not-fixed
Scleral search coils	-	Yes	No	High	Fixed
Video-oculography (VOG)	*Head-stabilized eye-tracking*	Yes	Yes	Medium	Fixed
	Remote/Screen-based eye-tracking	Yes	Yes	Low	Fixed
	Mobile/Head-mounted eye-tracking	Yes	Yes	Low	Not-fixed

interaction compared to head-stabilized eye-trackers. These systems often offer high levels of accuracy and precision, but they are not designed for mobility, so users must remain in a fixed position in front of the screen during eye-tracking sessions.

- *Mobile/Head-mounted eye-trackers*, which are designed to be worn by users, allowing for more natural and mobile eye-tracking experiences. They are often integrated into glasses, headsets, or helmets. Even if wearable eye-trackers may not match the precision of some screen-based systems, they are well-suited for real-world scenarios, such as studying gaze behavior in outdoor environments, assessing attention in driving, or analyzing eye movements during hands-on tasks. They can be also integrated into various devices, such as AR glasses, VR headsets, or safety goggles.

Table 1 summarizes the main features of the presented eye-tracking methodologies. VOG-based mobile eye-tracking is the most suitable method in dynamic contexts such as manufacturing, due to the presence of commercially unobtrusive solutions and the constant technological improvement of VOG. Although measurements may be less accurate than remote VOG eye-tracking, they are more than acceptable for real-world and naturalistic applications.

2.3 Eye-tracking applications in manufacturing

Eye-tracking technology is increasingly being used in manufacturing for various purposes, as it provides valuable insights and benefits across different aspects of the production process. Six main application areas can be identified:

- *Ergonomics and safety*. Eye-tracking is a valuable tool for studying ergonomics and human factors in manufacturing [15]. It can help identify ergonomic issues, safety hazards, and areas where workers may experience physical strain or discomfort [16]. Eye-tracking can be used to monitor worker attentiveness and detect signs of fatigue or distraction [17]. In safety-critical environments, this technology can provide real-time alerts or interventions when unsafe behaviors are detected, reducing the risk of accidents and injuries [18]. In addition, eye-tracking can provide insights into the cognitive workload experienced by workers during different tasks [19]. By analyzing eye movement patterns and pupil dilation, manufacturers can assess the mental effort required for specific job roles [20]. This information can aid in workload balancing and task allocation, ensuring that employees are not overwhelmed and maintaining overall productivity.

- *Human-machine interaction*. Eye-tracking helps manufacturers understand how operators interact with machinery (e.g., cobots) [21], control panels [22], and user interfaces [23]. Eye-tracking data can be used to optimize the design of these interfaces, making them more intuitive and user-friendly. By conducting usability testing and analyzing where users look and how their eyes move while performing tasks, design flaws and areas of improvement can be identified [24]. Improved user interfaces can reduce errors, increase efficiency, and enhance the overall user experience [25].
- *Production process analysis*. By analyzing the eye movements of workers on the factory floor, manufacturers can identify bottlenecks, inefficiencies, and areas where workers may be wasting time [26]. This data can inform process optimization efforts, leading to increased productivity and reduced production costs [27].
- *Training and skill development*. Eye-tracking can be used in training scenarios to understand how workers process information [28] and learn new tasks [29]. By analyzing their eye movements, trainers can identify areas where employees might struggle [30] and tailor training programs to address those specific challenges [31]. This can lead to faster skill acquisition and reduced training time [32].
- *Quality control and inspection*. Eye-tracking can be integrated into quality control [33] and inspection processes [34]. By monitoring where workers focus their attention during inspections, manufacturers can ensure that products are thoroughly examined [35] and meet the required quality standards [36]. This can reduce defects and improve overall product quality [37].
- *Product development*. Manufacturers can use eye-tracking to conduct research on how consumers interact with their products [38], packaging [39], and advertising materials [40]. This information can be valuable in improving product designs [41] and marketing strategies [42].

In summary, eye-tracking technology offers a range of benefits in manufacturing, from improving user interfaces and training programs to enhancing quality control and safety.

Table 2 provides an overview of the literature in the implementation of eye-tracking in long-duration sessions (e.g., work shifts) in the manufacturing context. The number of works in this area is still limited and most of them have focused in the area of quality control and inspection, as well as production process analysis. The use of eye-tracking in HRC for assessing operator status in entire work shifts is still quite limited.

2.4 Cognitive ergonomics and eye-tracking metrics

Cognitive ergonomics is a subfield of ergonomics that focuses on designing systems, products, and environments to optimize human cognitive performance and well-being [48]. It considers how humans perceive, process information, learn, remember, and make decisions in various contexts and aims to enhance these cognitive processes to improve overall system performance and user experience [49]. A key aspect of cognitive ergonomics is the mental workload management [50]. Mental workload refers to the cognitive demands placed on individuals during tasks, including overall strain experienced due to emotional or environmental factors [51]. Mental strain refers to the total and immediate impact within an individual resulting from a combination of stressors [52]. Therefore, effective workload management helps to ensure safe [53] and efficient performance [54].

Assessment of mental workload can be performed with classical subjective methods (e.g., questionnaires) or physiological methods (e.g., heart activity, electrodermal activity, and eye-tracking) [55]. The main advantage of using physiological methods, such as eye-tracking, over subjective methods is the continuous and naturalistic acquisition of information on the user state, without interfering with the process or task [56]. In addition, they can provide objective information on the user psychophysiological state [57].

Heart activity reflects the activity of the autonomic nervous system and can be easily monitored by electrocardiography (ECG) or photopletismography (PPG) signals [58], which can be acquired nowadays through minimally invasive devices such as bracelets or chest bands. Heart activity, particularly heart rate variability (HRV) [59], is often used to perform assessments on workload-related aspects such as fatigue and stress response in working contexts [60].

Electrodermal activity (EDA) measures changes in skin conductance due to sweat gland activity, which is influenced

Table 2 Literature overview on papers using eye-tracking in long-duration sessions in manufacturing

Papers	Application areas	Eye-tracking system	Eye-tracking metrics	Goal
Nandakumar et al. (2014) [43]	Ergonomics and safety	Mobile eye-tracking	- Pupil diameter - Fixation position	Assessment of mental workload
Ozkan and Ulutas (2016) [33]	Quality control and inspection	Mobile eye-tracking	- Total visit duration - Average visit duration - Number of visits - Total fixation duration - Average fixation duration - Number of fixations - Pupil diameter - Attention heatmap	Comparison of attentional patterns between novice and expert worker
Niemann et al. (2016) [44]	Quality control and inspection	Mobile eye-tracking	- Attention heatmap - Gaze plot	Assessment of operators' attention patterns
Haslgrübler et al. (2019) [31]	Production process analysis	Mobile eye-tracking	- Fixation position	Assessment of eye-hand coordination on precision tasks
Niemann et al. (2019) [35]	Quality control and inspection	Mobile eye-tracking	- Attention heatmap - Gaze plot	Assessment of operators' attention patterns
Puruzzini et al. (2020) [18]	Ergonomics and safety	Mobile eye-tracking	- Attention heatmap - Gaze plot - Pupil diameter	Assessment of mental workload
Straeter (2020) [19]	Ergonomics and safety	Mobile eye-tracking	- Pupil diameter	Assessment of mental workload
Tuncer et al. (2020) [36]	Quality control and inspection	Mobile eye-tracking	- Number of fixations - Total fixation duration - Attention heatmap	Assessment of operators' attention pattern
Ulutas et al. (2020) [37]	Quality control and inspection	Mobile eye-tracking	- Number of fixations - Total fixation duration - Number of visits - Average visit duration - Time to first fixation data - Attention heatmap	Comparison of attention patterns between novice and expert operators
Manns et al. (2021) [27]	Production process analysis	Mobile eye-tracking	- Fixation position	Identification and prediction of human intention
Nakamura et al. (2022) [45]	Production process analysis	Mobile eye-tracking	- Gaze plot	Comparison of attention patterns between a skilled workers and beginners
Cvahte Ojsteršek and Gajšek (2023) [46]	Human-machine interaction	Mobile eye-tracking	- Attention heatmap - Total duration of fixations - Average duration of fixations - Number of fixations - Total duration of visits - Average duration of visit - Number of visits	Evaluating operator's attentional pattern in a polishing process with a cobot
Nakamura and Komiya (2023) [47]	Quality control and inspection	Mobile eye-tracking	- Gaze plot	Comparison of gaze patterns between a skilled worker and a beginner

by sympathetic nervous system arousal [61]. EDA measurements are typically performed using specialized sensors or electrodes that are attached to the skin. Increases in EDA are directly related to increased arousal, which may result from the use of cognitive resources or from particular affective states [60]. Therefore, monitoring EDA can provide real-time feedback on workers' emotional and cognitive states, helping to identify periods of high mental strain.

Brain activity is usually monitored through electroencephalography (EEG), which records electrical activity in the brain, providing insights into cognitive processes and mental states [62]. Different EEG frequency bands (e.g., alpha, beta, theta) can be associated with specific mental states, such as relaxation, alertness, or mental fatigue [60]. Compared with other psychophysiological parameters, the EEG can provide richer information about a worker's cognitive processes. However, acquisition of this signal often requires the application of invasive electrodes on the head, and in addition, the EEG signal is quite sensitive to artifacts from movements which require special attention during analysis [63].

Eye-tracking, in comparison with other psychophysiological methodologies, potentially represents a good trade-off between richness of information obtainable about cognitive processes and invasiveness of the acquisition tool. Multiple metrics can be obtained simultaneously, providing a rather broad view of a user's mental processes. In addition, eye-tracking can also be seamlessly integrated into AR or VR devices that are typically used to assist the operator or enable communication in the HRC [9]. In the literature, eye-tracking metrics have been used to effectively measure workload [64], and multiple measures have shown some validity [65]. The most common measures for workload are reported in Table 3. In interpretations of these metrics, it is important to take into consideration the context of the phenomenon under analysis [66]. Aspects such

Table 3 Common eye-tracking metrics and their interpretation

Category	Eye-tracking metric	Description	Interpretation	References
Fixation	*Number [-]*	The number of fixations, usually in a certain area of interest (AOI).	The number of fixations approximates visual attention allocation. The more fixations can equate to less efficient search or increased visual effort, thus higher mental workload.	[64, 65, 68]
	Duration [ms]	The time spent gazing at a position.	A longer fixation duration describes issues related to extracting information (i.e., more processing time), or it indicates that the target is more appealing.	[46, 64, 65]
	Position (gaze position) [mm, °, pixels]	Location of fixations, usually represented in cartesian coordinates.	Used mostly in attentional studies, to understand whether certain areas are being observed or not.	[27, 69]
Saccade	*Number [-]*	The number of saccades, usually in a certain AOI.	Higher number of saccades can be associated to higher visual effort, thus higher mental workload.	[64, 65]
	Duration [ms]	The length of time from the start to end of a saccade event (i.e., shifting from a fixation to another)	Longer saccade durations indicate decreased processing and more visual search activity.	[64, 65]
	Amplitude [°]	The measure of visual arc degrees of movement from one fixation to the next.	Saccade amplitude usually drops as mental workload increases.	[64, 65]
	Velocity [°/s]	The speed of the saccade (degrees/time), usually measured considering the peak velocity.	Average peak saccadic velocity tends to decrease as mental workload increases, especially when sustained attention is required.	[70–72]
Pupil	*Size [mm, mm^2]*	Diameter or area of the pupil.	Pupil size in adults can range between 2 mm and 8 mm in diameter. Higher pupil size can be associated to higher mental demand.	[64, 65, 68]
Blink	*Rate [1/s]*	Blink frequency per minute or second	Higher blink rates can be associated with higher mental demand or fatigue [36], while lower blink rates can be associated to higher visual demand or attention [32].	[65, 68, 73]
	Duration [ms]	Closure time duration of a blink	Lower blink duration may be associated to higher visual demand, while higher blink duration can be provoked by tiredness or fatigue.	[64, 73]
Visit	*Number [-]*	Number of visits to an AOI.	Higher number of visits can be associated to higher attraction to a certain AOI (for better or worse)	[33, 37, 46]
	Duration (dwell time) [s]	Time spent in an AOI.	High visit duration can be associated to high attention or visual effort in a certain AOI.	[33, 37, 74]
Aggregation	*Attentional heatmap*	Visualization through heatmap of the number of times attention was to a particular area.	Used mostly in attentional studies, to understand the attention distribution in an AOI	[64, 69]
	Gaze plot (or scanpath)	Representation of a chronological sequence of fixations with their duration describing visual behavior in a AOI	Used to analyze visual interaction patterns.	[64, 69]
	Saccade-fixation ratio (SF ratio)	The ratio of the durations of saccades to fixations.	Lower ratios correspond to either more processing or to less search activity.	[64, 65]

as environmental conditions and task type can influence the variability of eye-tracking metrics [67].

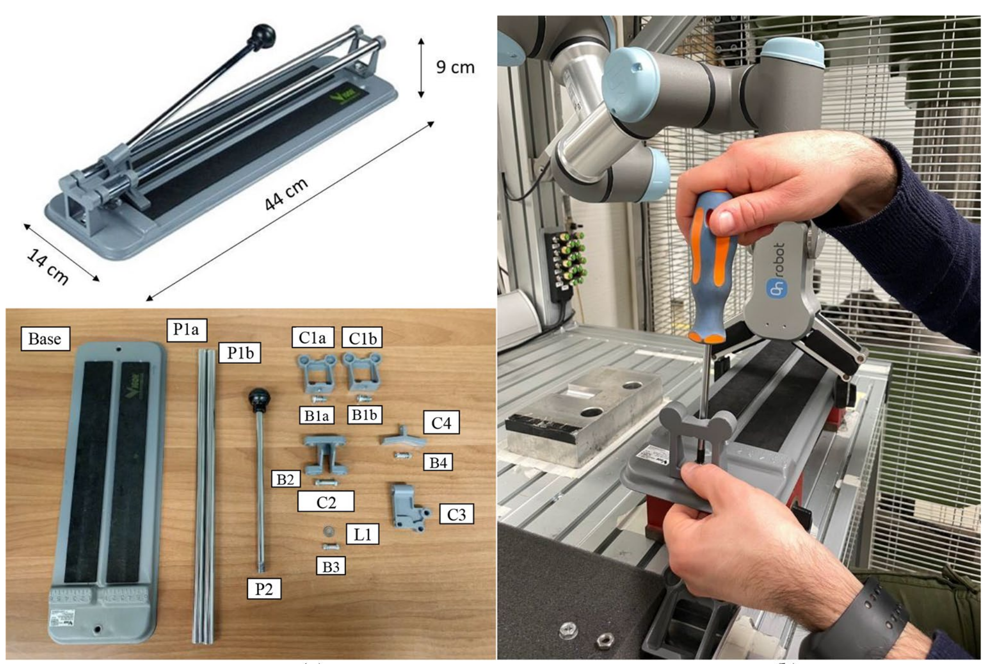
3 Example case study: Eye-tracking in a repetitive HRC assembly process

In this section, a case study involving the use of a wearable eye-tracking device in naturalistic and dynamic setting in the context of HRC is provided, as well as an example of concordance between different eye-tracking metrics. This example serves to highlight what information can be acquired by eye-tracking during an HRC process and how certain metrics may be better suited to show certain phenomena related to mental strain.

To investigate the mental effort involved in a repetitive HRC assembly process, 8-hour shifts of a tile cutter assembly process were designed and implemented using the cobot UR3e (Fig. 3). The 8-hour shift was divided in two 4-hour shifts: one in the morning and the afternoon. Six participants (three males and three females, between the age of 20 and 21) who had no prior experience with cobots were involved and performed the assembly process shifts in HRC modality (i.e., with the cobot). The absence of prior experience with cobots allowed also to observe the learning effect during the shift. The assembly process can be decomposed in the following four main steps:

1. *Assembly of the side supports.* The cobot brings the base of the tile cutter closer to the operator, who assembles the side supports for the rail rods. When the operation is finished, the cobot sets the assembled component aside.
2. *Assembly of the cutting mechanism*. The cobot takes the main component of the cutting mechanism and holds it in an ergonomic position in front of the operator. The operator positions and assembles the round blade and the remaining two components of the mechanism. When the operations are finished, the cobot releases the cutting mechanism close to the operator.
3. *Assembling the base with the cutting mechanism.* The cobot brings the base with assembled side supports back to the operator; the operator picks up the cutting mechanism, inserts the rail rods through the appropriate slots of the cutting mechanism, and joins the rail rods to the base through the side supports.
4. *Completion of the tile cutter*. The operator takes the handle and inserts it into the threaded slot of the cutting mechanism. When finished, the cobot takes the completed tile cutter and sets it aside.

During the performance of the shifts, the Tobii Pro Glasses 3 (Fig. 2b) device was worn by participants to collect eye-tracking data during the assembly process. Observations collected for two participants were excluded due to loss of eye-tracking data during the recording. For one participant, the collected data from one shift were found to be corrupted, while for the other, the device accidentally turned off during one shift, thus interrupting data collection, without being noticed. The software Tobii Pro Lab was used to elaborate eye-tracking data and extract eye-tracking metrics. Four of the most common metrics were analyzed in the case studies:



(a) (b)

Fig. 3 - Tile cutter to be assembled and its components (**a**), and the assembly process with the cobot UR3e (**b**) [78]

average pupil diameter, number of fixations, average duration of fixations, and number of saccades. Each of these metrics is reported by manufactured product (*Trial*). Each person may have different ranges of values for these metrics (Fig. 4) due to personal characteristics (e.g., one person may have greater pupillary dilation than another with the same conditions). In order to remove potential influence of personal characteristics and allow a better comparison of the results, for each metric, z-scores were calculated for each participant using the following formula:

$$z_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j} \tag{1}$$

where z_{ij} is the z-score *i* for participant *j*, x_{ij} the observation *i* for participant *j*, $\overline{x}_j$ the sample mean for participant *j*, and s_j the sample standard deviation for participant *j*. To statistically compare the values obtained from the various eye-tracking metrics in the two shifts and their phases, the Wilcoxon signed-rank test was used [75]. This nonparametric test was chosen since the normality assumption was rejected by the Shapiro-Wilks test for each metric and it is suitable for comparing paired data.

A 10-minunte break was taken every two hours, where the NASA-TLX questionnaire [76] was administered to collect the perceived workload. NASA-TLX includes six dimensions that are required to be evaluated: *Mental demand*, *Physical demand*, *Temporal demand*, *Performance*, *Effort*, and *Frustration* (Fig. 5). Each dimension is rated on a scale between 0 and 100 with 5-point steps, and the final workload score is obtained by averaging the dimension ratings. Workload score values can be interpreted as follows: 0–9 as low, 10–29 as medium, 30–49 as somewhat high, 50–79 as high, and 80–100 as very high [77].

A one-hour lunch break was taken between the morning and afternoon shifts. The assembly of a tile cutter lasted about 240s, leading to the production of about 120 products (60 in the morning and 60 in the afternoon) in an 8-hour shift.

Figure 6 shows the results of NASA-TLX. In general, as expected, the perceived *Workload* increased with time. In particular, gradual increases in *Physical demand*, *Temporal demand*, *Effort* and *Frustration* can be observed along the shift. *Performance* is a reverse item, consequently the higher the value, the lower the participant's perceived degree of success in completing a task. In the present case, it can be observed that in the second part of both the morning and afternoon shifts there was a decrease in perceived performance, probably due to a sense of fatigue. Observing at *Frustration*, an increasing trend can be observed over time, with a greater increase in negative feelings in the afternoon shift mainly derived from a sense of fatigue. For *Mental Demand*, a consistent increase can be seen between the morning and afternoon shifts. Based also on participants' feedback, the morning shift was mainly characterized by the use of mental resources for learning the assembly process, while the afternoon shift was characterized by a general sense of fatigue and frustration, leading to the phenomena of mental satiation and mental fatigue. It is also interesting to note the difference between the first and second parts of the four-hour shift, both in the morning and afternoon. This suggests that starting a shift required the use of more mental resources than continuing it in the second part. These phenomena related to *Mental demand* will be investigated through eye-tracking metrics.

Looking at the evolution of the average pupil diameter across participants along the shift (Fig. 7), a pattern rather similar to what was observed for the NASA-TLX *Mental Demand* dimension can be seen. At the beginning of the morning shift, a greater pupil dilation was observed, indicating a significant amount of mental resource use. This was mainly due to a learning phase, in which participants had to familiarize themselves with the assembly process by trying to remember the various steps. As the trials continued, the average pupil diameter decreased, indicating a gradual decrease in the use of mental resources, mainly due to the repetitiveness of the process. Observing the afternoon shift, significant higher values emerged compared to the morning shift (Wilcoxon signed-rank test, $p < 0.001$). In addition, a behavior very similar to the morning shift was observed. At the beginning, rather high pupillary dilation values were again observed, similar to those at the beginning of the morning shift, which then gradually decreased along the shift. This phenomenon highlights that having to start the shift over again required the use of different mental resources, probably due not only to remembering how to perform the assembly but also to stress.

Figure 8 shows the evolution of the number of fixations across participants over trials. A rather high number of fixations was observed at the beginning of the morning shift, indicative of a consistent use of mental resources due to learning the assembly process. As the shift continued, the number of fixations decreased significantly. However, higher values were observed at the beginning of the afternoon shift than at the end of the morning shift, probably due to having to resume the process. Along the shift there was a gradual decrease, however after the mid-afternoon shift break a slight increase in the number of fixations was observed, which decreased again as the trials continued. Comparing the first half of the two shifts (i.e., morning and afternoon), significant higher values were observed in the morning shift (Wilcoxon signed-rank test, $p < 0.001$). However, observing the second half of the two shifts, significantly higher values

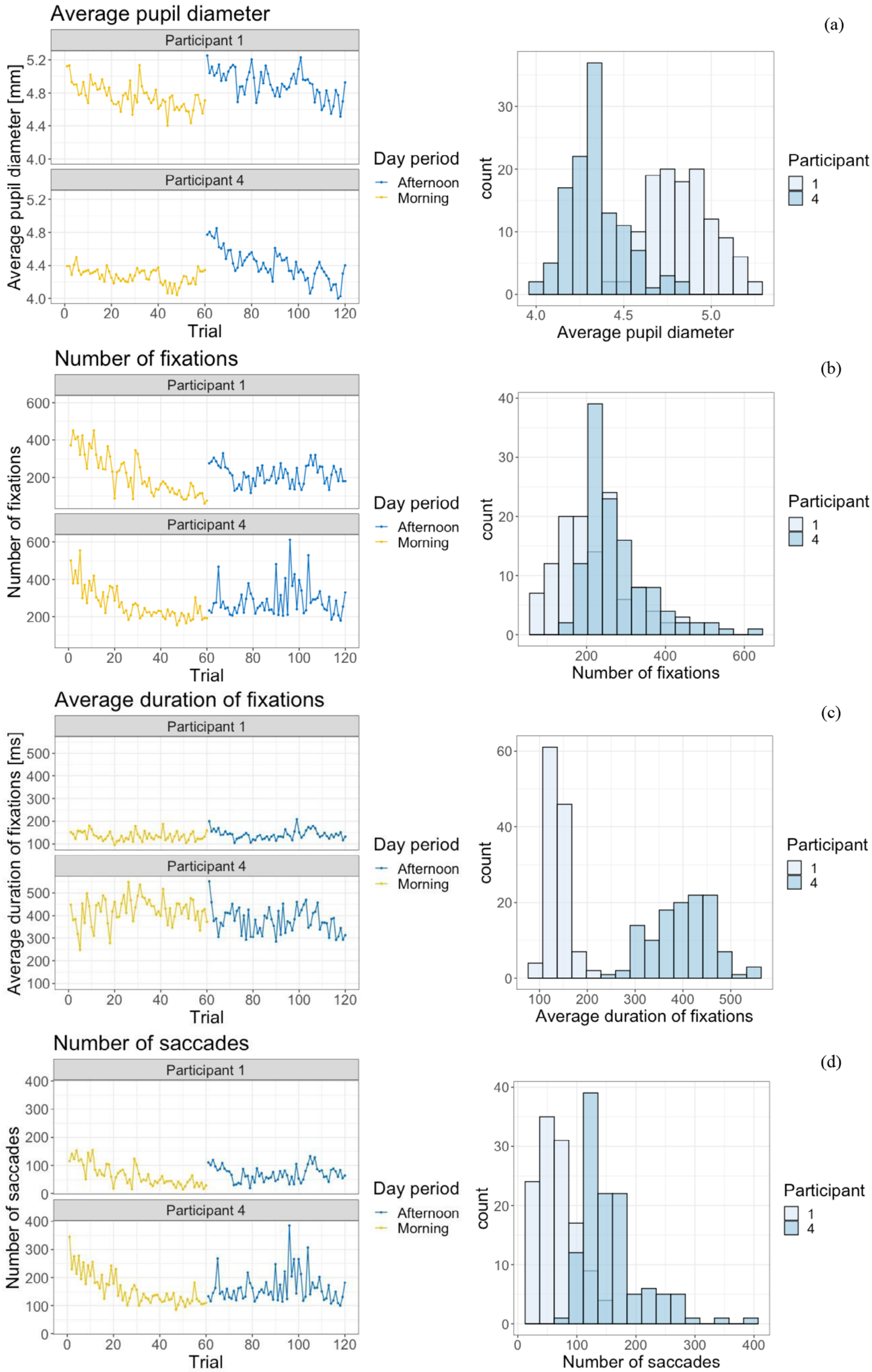


Fig. 4 Example of differences in eye-tracking metrics distribution between participants. Average pupil diameter (**a**), number of fixations (**b**), average duration of fixations (**c**), and number of saccades for participants 1 and 4

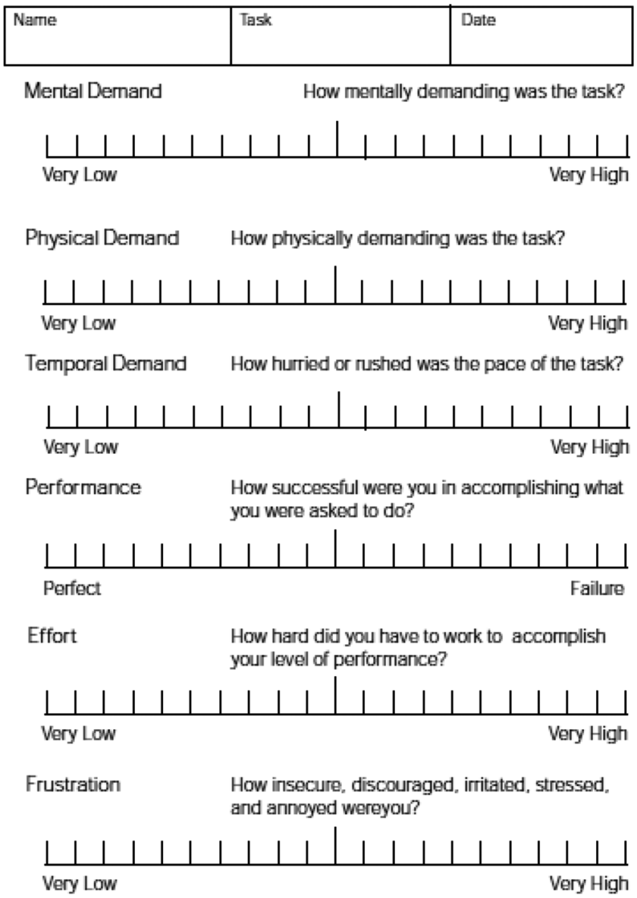


Fig. 5 NASA-TLX questionnaire and its six dimensions [76]

were present in the afternoon shift (Wilcoxon signed-rank test, $p<0.001$) which can be due to a general fatigue of operators.

The evolution of the average duration of fixations across participants across the shift is contained in Fig. 9. A decreasing trend was observed in the morning shift, indicating a steady decrease in the mental resources required by the process. However, at the beginning of the afternoon shift, the average duration of fixations was found to be significantly high. This fact points to an effect mainly due to mental fatigue resulting from having to start the process again after the lunch break. Along the afternoon shift there was a gradual decrease in the average duration of fixations. No significant difference emerged in terms of values between the afternoon and the morning shift according to the Wilcoxon signed-rank test ($p=0.5$).

Figure 10 illustrates the evolution of the number of saccades among participants throughout the trials. At the beginning of the morning shift, a notable number of saccades were observed, indicating a consistent utilization of mental resources as participants familiarized themselves with the assembly process. As the shift progressed, a substantial reduction in the number of saccades was observed. At the beginning of the afternoon shift, higher values were observed compared to the end of the morning shift, likely due to the need to reacquaint with the process after the lunch break. Over the course of the shift, a gradual decrease occurred. However, following the mid-shift break, an upturn in the number of saccades was observed, which subsequently decreased as the trials progressed. By comparing the

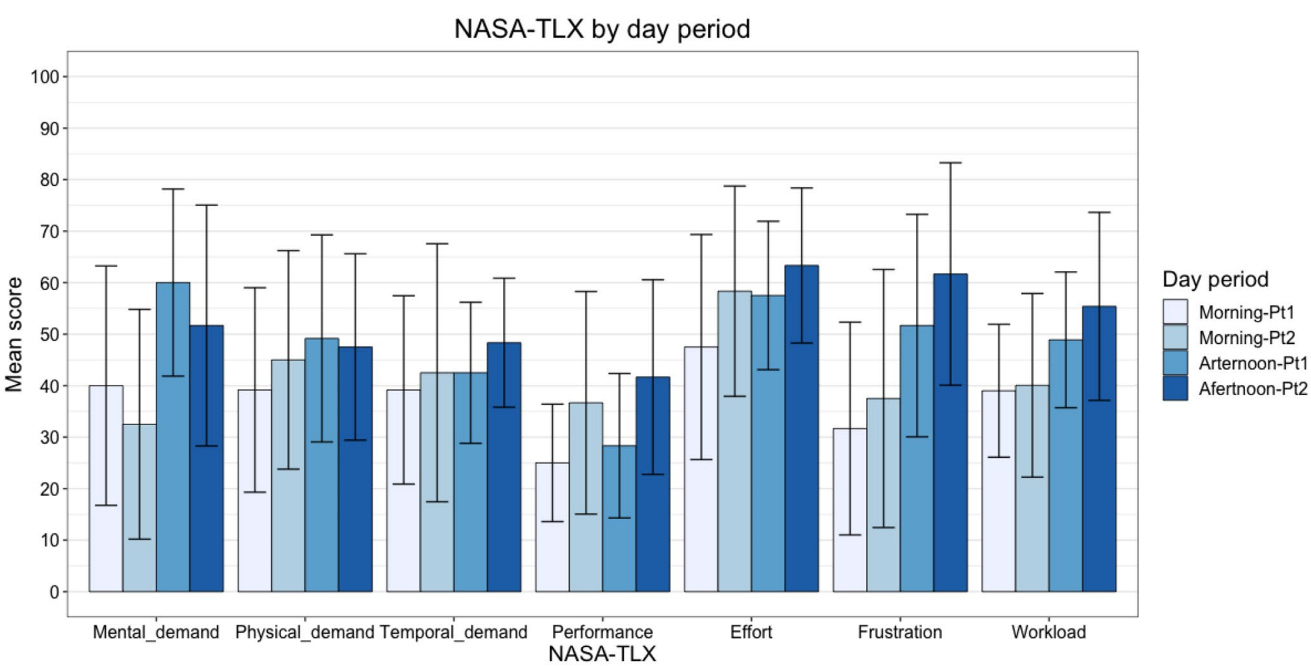


Fig. 6 Average score and standard deviation of NASA-TLX dimensions across day periods of the shift

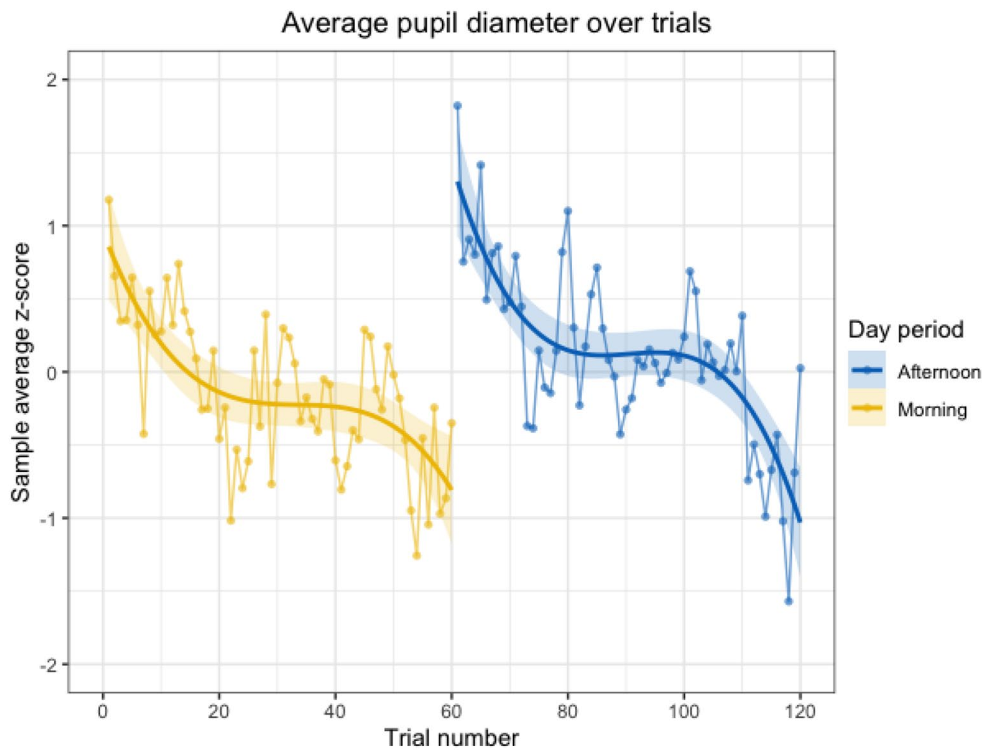


Fig. 7 Evolution of the standardized average pupil diameter during the HRC assembly shift. Underlying trends with confidence bands are highlighted

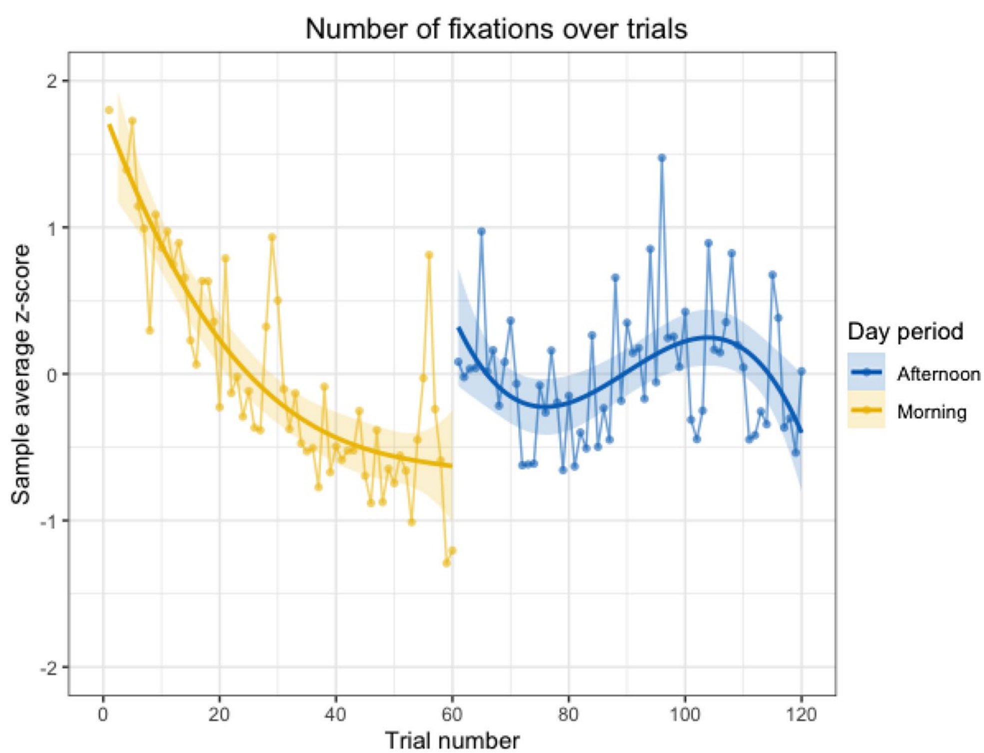


Fig. 8 Evolution of the standardized number of fixations during the HRC assembly shift. Underlying trends with confidence bands are highlighted

first half of the morning and afternoon shifts, significantly higher values were observed in the morning shift (Wilcoxon signed-rank test, $p < 0.001$), highlighting a higher mental strain deriving from the learning phase. However, looking at the second half of the shifts, significantly higher values were present in the afternoon shift (Wilcoxon signed-rank test, $p < 0.001$).

To explore the concordance between the eye-tracking metrics, the correlation between them in both the morning and afternoon shifts was analyzed (Figs. 11 and 12). Pearson's correlation coefficient is the most common indicator

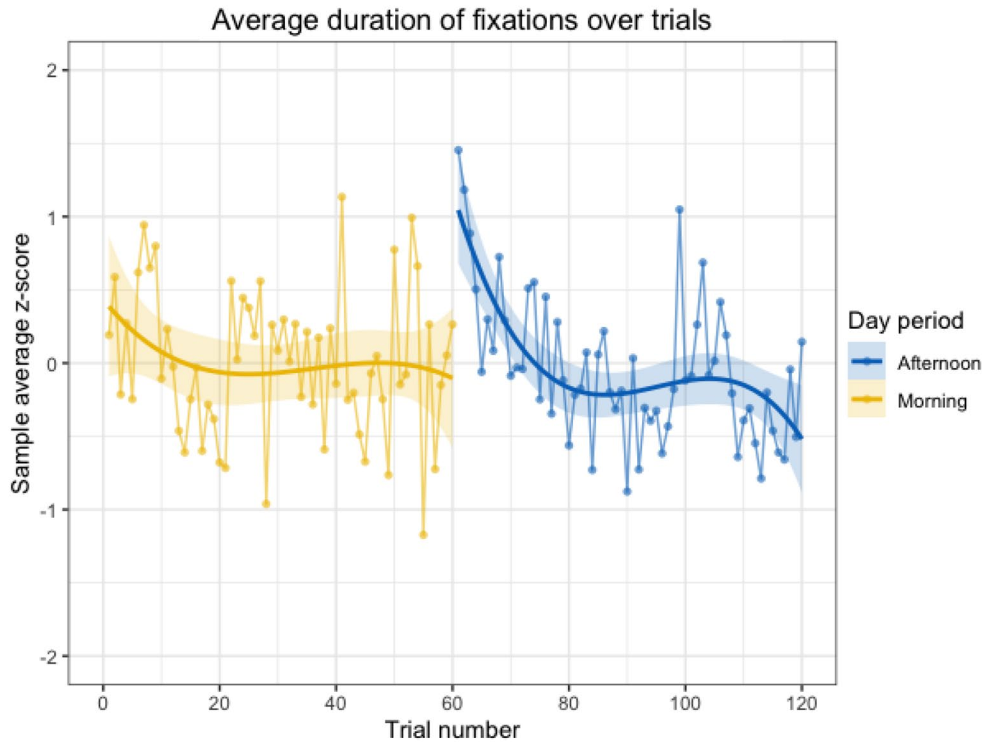


Fig. 9 Evolution of the standardized average duration of fixations during the HRC assembly shift. Underlying trends with confidence bands are highlighted

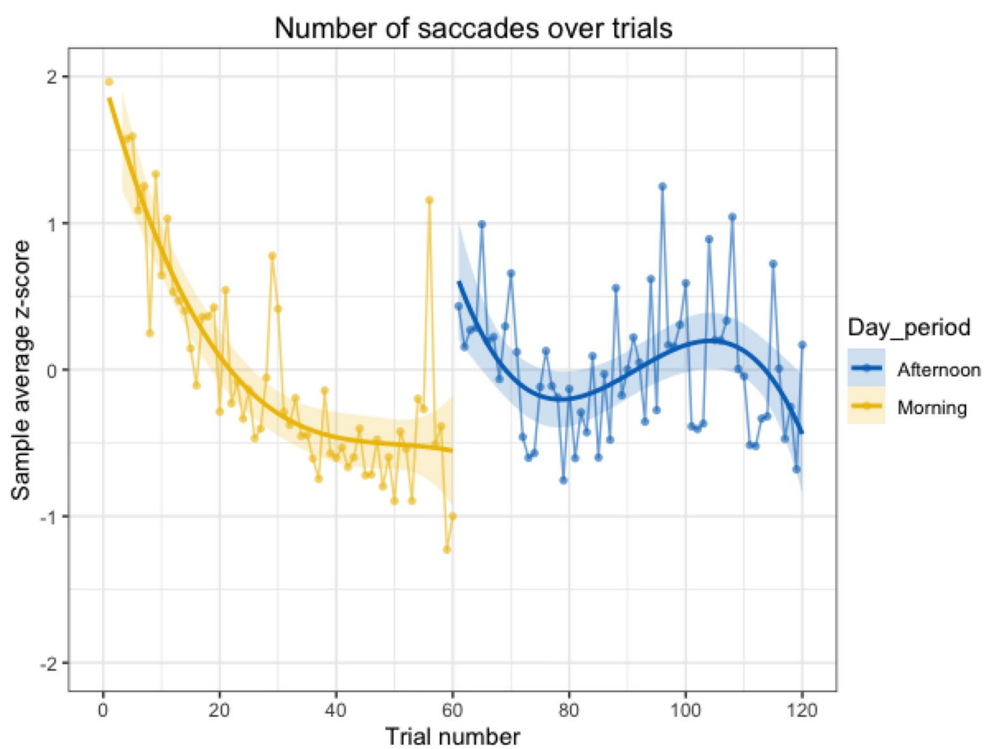


Fig. 10 Evolution of the standardized number of saccades during the HRC assembly shift. Underlying trends with confidence bands are highlighted

for measuring correlation among two variables [79]. It varies between − 1 and 1, representing both the direction and strength of the relationship between two variables. A negative value represents a negative correlation (i.e., when one variable changes, the other variable changes in the opposite direction); conversely, a positive value means a positive correlation (i.e., when one variable changes, the other variable changes in the same direction). The absolute value of the indicator represents the strength of the correlation: the closer it is to 1, the stronger the correlation. Absolute values between 0 and 0.3 identify a weak correlation, between 0.3 and 0.7 a moderate correlation, and between 0.7 and 1 a

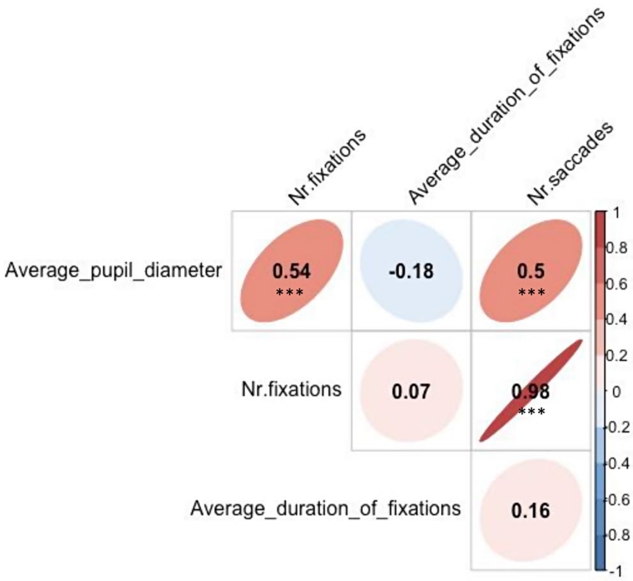


Fig. 11 Pearson's correlation coefficients between eye-tracking metrics during the morning shift. Significance of the correlation is reported as follows: (*) $0.05 > p \geq 0.01$, (**) $0.01 > p \geq 0.001$, (***) $p < 0.001$

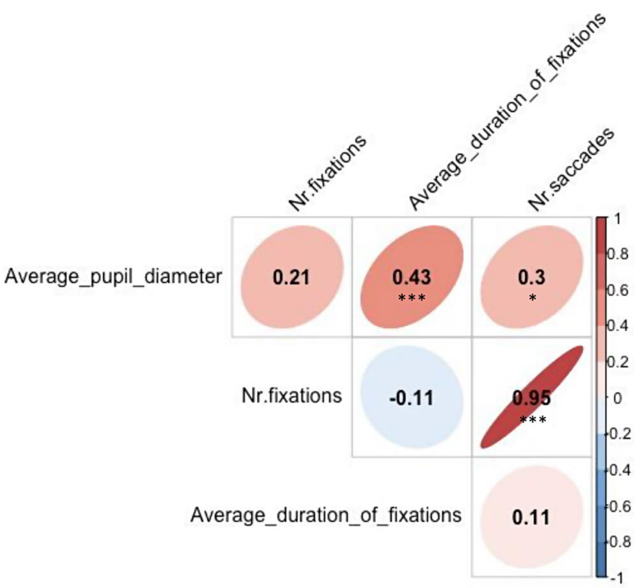


Fig. 12 Pearson's correlation coefficients between eye-tracking metrics during the afternoon shift. Significance of the correlation is reported as follows: (*) $0.05 > p \geq 0.01$, (**) $0.01 > p \geq 0.001$, (***) $p < 0.001$

strong correlation. As can be seen, the number of fixations and the number of saccades are highly correlated in both the morning and afternoon shifts. This phenomenon was expected, as the gaze path is usually composed of an alternating sequence between fixations and saccades. Focusing on the morning shift (Fig. 11), a moderate correlation can be seen between the average pupil diameter and the number of saccades, as well as between the average pupil diameter and the number of fixations. During this period of the day, most of the operators' mental resources were spent on learning the assembly process, and this phenomenon clearly emerged from the analysis of the metrics under consideration. Interestingly, in the afternoon shift (Fig. 12) these correlations (i.e., "average pupil diameter - number of fixations" and "average pupil diameter - number of saccades") decreased dramatically, while a moderate one emerged between average pupil diameter and average duration of fixations. These two metrics particularly emphasized mental strain due mainly to having to resume the assembly process and manage mental fatigue.

4 Discussion

The literature review showed that the exploration of integrating eye-tracking technology into production processes is quite recent. Eye-tracking has shown great promise for studying and improving worker efficiency and well-being, user interfaces, and manufacturing strategies. Particularly in the field of cognitive ergonomics, it offers a non-invasive solution to study manufacturing processes and HRC in a naturalistic manner. In addition, compared with methods that allow the collection of rich psychophysiological information, such as EEG, recent technological developments in the field of eye-tracking offer wearable solutions that are more comfortable and less invasive for the operator, with a rather quick and simple setup. These aspects proved functional for greater deployment and use in manufacturing. However, from the literature emerged that at present there are few studies on HRC in long sessions that explore aspects related to mental workload. Eye-tracking has the potential to support in-depth study of such aspects, offering various psychophysiological information acquired in a naturalistic manner even in long-duration sessions, thus not hindering human interaction with cobots. In addition, it can be integrated in AR or VR devices that are often used to support the interaction with cobots.

The case study presented showed an example of eye-tracking application in long sessions in the HRC setting to highlight phenomena related to mental strain that can occur during a work shift. In particular, key eye-tracking metrics were explored in an 8-hour repetitive HRC assembly process divided into two 4-hour shifts. Participants reported no discomfort in using the eye-tracking glasses; only some participants who were not used to wearing glasses experienced slight discomfort at first. All metrics were sensible to cognitive load and showed a pattern in line with the collected responses related to the *Mental demand* dimension of NASA-TLX, therefore resulting in more mental strain in the afternoon shift than in the morning one. In details, the morning shift was mainly characterized by a learning phase, whereas the afternoon shift was more influenced by resuming the process and mental fatigue. This pattern is in line with findings of previous works dealing with repetitive processes, such as [78] and [80]. One notable observation is the adaptation of cognitive resources over time, especially in the morning shift. Participants exhibited a high pupil dilation, number of fixations and saccades during the initial phases of the process. This can be attributed to the cognitive demands imposed by the need to acquire and internalize the assembly process. However, as the shift progressed, a substantial decrease in pupil dilation, number of fixations and saccades occurred, signifying a more streamlined cognitive process. These findings underscore the adaptability of human cognition in manufacturing HRC settings. In addition, the significant correlations that emerged between these three eye-tracking metrics gives more robustness to the results obtained. Finally, participants' mental fatigue was detected quite well by both pupillary dilation and average duration of fixations, indicating their adequacy in monitoring this aspect [81], and a significant correlation emerged between these two metrics during the afternoon shift. This fact highlights the possibility to detect through pupil dilatation mental strain resulting from learning as well as mental fatigue. This result is in line with results of previous works concerning repetitive processes, such as [19] and [82]. Therefore, relying on a single eye-tracking metric may provide a limited perspective on mental processes. By considering a combination of different metrics concurrently, a more comprehensive view on visual attention and mental strain can be gained. In addition, the convergence of different eye-tracking metrics can enhance the sensitivity to variations in mental strain, allowing for a deeper analysis of cognitive dynamics.

5 Conclusions

The implementation of eye-tracking technology in manufacturing provides great potential for optimizing cognitive ergonomics and enhancing overall performance and operator's well-being. From an ergonomic point of view, eye-tracking metrics provide important information about operators' mental effort without having to interrupt the manufacturing process. This aspect is particularly useful for naturalistic analysis of HRC, in which humans are actively involved in the interaction with the cobot. Recent wearable eye-tracking devices allow the simultaneous collection of multiple information regarding fixations, saccades, and pupillary dilation, making it possible to highlight and distinguish different phenomena related to mental strain (e.g., activation, learning, stress response, or mental fatigue). In addition, compared with other methods that allow to collect rich psychophysiological information, such as EEG, eye-tracking is less invasive with a faster setup and has the potential of being seamlessly integrated into wearable AR or VR devices. Together, these features make eye-tracking particularly attractive for the naturalistic study of HRC in manufacturing, especially in long-duration sessions, although there are currently a limited number of studies implementing it.

The example case study presented highlighted the reliability of eye-tracking in effectively detecting the mental strain, even in dynamic and prolonged tasks such as a repetitive HRC assembly process. In addition, through the analysis of multiple eye-tracking metrics, different phenomena related to mental strain were highlighted. The number of fixations and saccades were particularly useful in highlighting the mental resources expended during learning, while the average duration of fixations better emphasized mental fatigue. The average pupil diameter was sensitive in detecting mental strain due to both learning and mental fatigue. This fact suggests that pupillary dilation which may be a good first indicator to detect general increases in mental strain.

In general, through the case study, it emerged the importance in taking into account and analyze not just a single eye-tracking metric, but multiple metrics, while also evaluating the concordance among them. This kind of approach can provide a clearer overview of the mental strain generated by the intricate interplay between cognitive and emotional dynamics, contributing to a more insightful exploration of the operator's experiences.

A limitation of the example case study is the lack of integration of AR tools, although the purpose of the case study presented was to ascertain and show the ability of eye-tracking to detect various phenomena related to mental workload (such as learning, mental fatigue) and the noninvasiveness in their detection in the HRC setting. Future work will focus on exploring the integration of the level of technology offered by the latest eye-tracking devices for monitoring psychophysical state into devices designed to support operator and communication during interaction with cobots. Looking forward, such integration may support the development of an operator's "digital twin" that also takes into account the operator's psychophysical state, aimed at enhancing the operator's well-being in HRC.

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Author contributions R.G., M.C., L.M., F.F. contributed to the study conception and design. Material preparation, data collection and analysis were performed by R. G. and M. C. The first draft of the manuscript was written by R. G.and M. C. under the supervision of L. M.and F. F. All authors read and approved the final manuscript.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Ethical approval The authors respect the Ethical Guidelines of the Journal.

Consent for publication Not applicable.

Consent to participate Informed consent was obtained from all individual participants included in the study.

Conflict of interest The authors declare that they have no conflict of interest.

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