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Opportunities for using eye tracking technology in manufacturing and logistics: Systematic literature review and research agenda

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A R T I C L E I N F O

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A B S T R A C T

Workers play essential roles in manufacturing and logistics. Releasing workers from routine tasks and enabling them to focus on creative, value-adding activities can enhance their performance and wellbeing, and it is also key to the successful implementation of Industry 4.0. One technology that can help identify patterns of worker-system interaction is Eye Tracking (ET), which is a non-intrusive technology for measuring human eye movements. ET can provide moment-by-moment insights into the cognitive state of the subject during task execution, which can improve our understanding of how humans behave and make decisions within complex systems. It also enables explorations of the subject's interaction mode with the working environment. Earlier research has investigated the use of ET in manufacturing and logistics, but the literature is fragmented and has not yet been discussed in a literature review yet.

This article therefore conducts a systematic literature review to explore the applications of ET, summarise its benefits, and outline future research opportunities of using ET in manufacturing and logistics. We first propose a conceptual framework to guide our study and then conduct a systematic literature search in scholarly databases, obtaining 71 relevant papers. Building on the proposed framework, we systematically review the use of ET and categorize the identified papers according to their application in manufacturing (product development, production, quality inspection) and logistics. Our results reveal that ET has several use cases in the manufacturing sector, but that its application in logistics has not been studied extensively so far. We summarize the benefits of using ET in terms of process performance, human performance, and work environment and safety, and also discuss the methodological characteristics of the ET literature as well as typical ET measures used. We conclude by illustrating future avenues for ET research in manufacturing and logistics.

1. Introduction

Providing customized, high-quality products at a reasonable price is crucial for manufacturing companies to remain competitive in today's environment. Two essential capabilities that are required to satisfy customer needs are manufacturing flexibility and logistics efficiency (Tracey, 1998). Manufacturers that do not strategically build and exploit these capabilities (e.g., by cost reduction or process improvement measures) may lose their competitive advantage.

Even though manufacturers have steadily increased the degree of automation of their manufacturing and logistics processes to reduce costs, the growing level of product customization and shortening product lifecycles often make it difficult to redeem the investments fully automated systems require (Romero et al., 2020). Moreover, some operations are inherently difficult to automate, e.g., assembly processes or maintaining customized complex equipment, where the sensorimotor abilities of human workers that machines cannot imitate yet lead to performance advantages (Neumann et al., 2021). Thus, many companies

Abbreviations: AM, Additive Manufacturing; AOI, Area of Interest; AR, Augmented Reality; EEG, Electroencephalography; EMG, Electromyography; EOG, Electro-Oculography; ET, Eye Tracking; FI, Feedforward Information; GSR, Galvanic Skin Response; NNI, Nearest Neighbour Index; POG, Photo-Oculography; POR, Point of Regard; PST, Pupil Graphic Sleepiness Test; RLS, Robot Light Skin; SA, Situational Awareness; SAGAT, Situation Awareness Global Assessment Technique; SART, Situational Awareness Rating Technique; SF, Saccade Amplitude Fixation Duration; SRL, Supernumerary Robotic Limbs; UML, Unified Modeling Language; VOG, Video-Oculography; VR, Virtual Reality; WoS, Web of Science.

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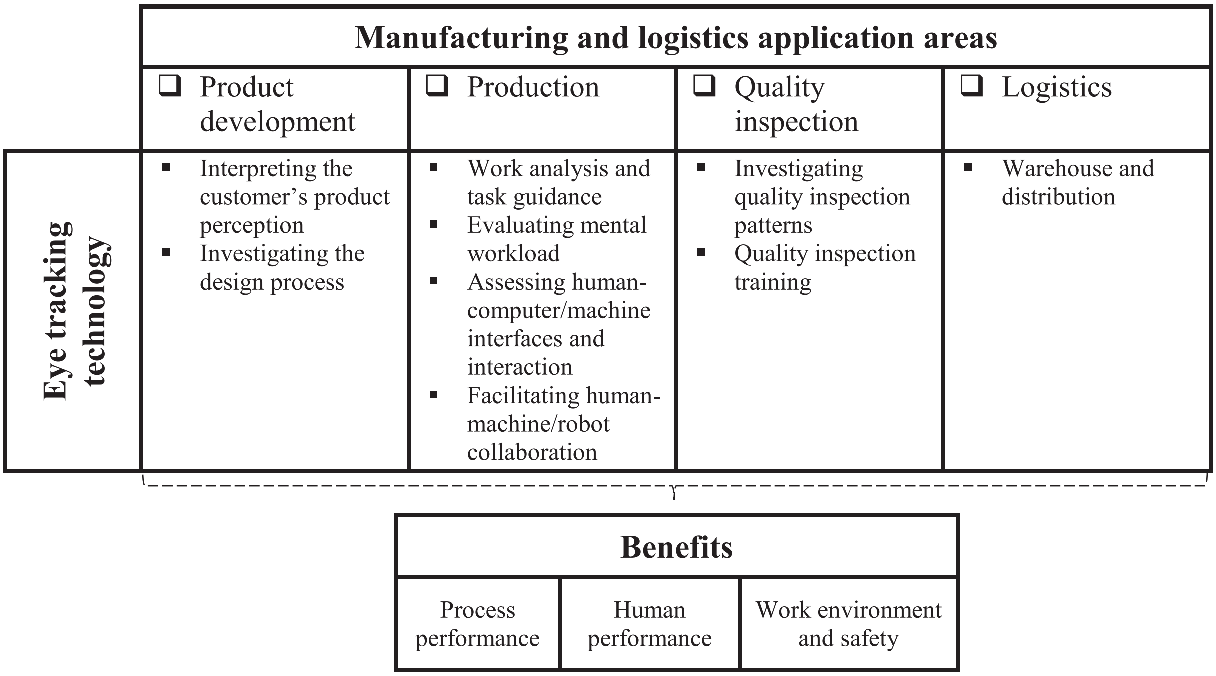

Fig. 1. Conceptual framework used for classifying the literature.

still rely on a large amount of manual work, especially in areas such as material handling and assembly (Sgarbossa et al., 2020). In the last decade, the way humans are involved in and interact with the manufacturing and logistics environment has changed as a result of Industry 4.0, which is characterised by intelligent networking of humans, machines and processes with the help of information and communication technologies, such as cyber-physical systems, the internet of things, big data analytics, or cloud-based systems (Kagermann et al., 2013; Neumann et al., 2021; Raut et al., 2020). Manufacturing and logistics systems are socio-technical systems that pair humans and technologies to satisfy the system's productivity requirements and the socio-psychological needs of the individuals involved (Blumberg & Alber, 1982; Sgarbossa et al., 2020). Improving human-technology compatibility in socio-technical systems enables individuals to enjoy greater responsibility and enhances their personal development, which, in turn, improves system performance (Neumann et al., 2021). Indeed, releasing workers from routine tasks and enabling them to focus on creative, value-adding activities within a socio-technical system is key to the successful implementation of Industry 4.0 (Kagermann et al., 2013; Winkelhaus et al., 2021). Using new technologies to assist workers and to adapt production processes to their needs is also the key vision of Industry 5.0 (Breque et al., 2021; Dixson-Declève et al., 2022). To ensure that workplaces and processes match the requirements of workers, it is necessary to analyse how workers interact with their work environment. One technology that can potentially support such an analysis is ET.

Traditional measurements of human-technology compatibility use, for example, psycho-physiological indicators (e.g., heart rate, electromyography, or perceived human exertion) or indirect indicators (e.g., injury rates, economic losses, or operational effectiveness). In contrast to that, ET can provide moment-by-moment insights into the cognitive state of the subject during task execution in a non-intrusive way. ET captures eye motion and gaze in response to a stimulus object and can improve our understanding of how humans behave and make decisions within complex systems. It reflects the user's visual attention, helps to quantify precisely where, how, and in which order gaze is being directed, and provides cues to gather information on a person's intentions and current mental state (Pfeiffer et al., 2020). Recent research has used ET to assess and improve human performance in various areas, for example by studying a subject's situational awareness (SA) in aviation or road traffic (Peißl et al., 2018), by investigating a subject's learning and mental state during training (Rosch & Vogel-Walcutt, 2013), and by improving the expertise level for clinical surgery (Sharma et al., 2016). In manufacturing and logistics, ET has been used to detect the information extraction efficiency in a production workspace (Stork et al., 2007), to predict a subject's intention and the subsequent steps of a task (Bovo et al., 2020), to indicate mental workload under varying conditions (Straeter, 2020), or to generate input for robot control in collaborative work scenarios (Paletta et al., 2019). ET can help in identifying worker skills (Haslgrübler et al., 2019) and inefficiencies in operational processes (Tuncer et al., 2020), which generates valuable insights into options for improving human and process performance.

While ET has been applied quite frequently in various disciplines, its potential in manufacturing and logistics has not been surveyed in a structured literature review yet. We are only aware of two papers that attempted to give an overview of possible ET applications in manufacturing, but none of them comprehensively discussed how ET can be used in manufacturing and logistics and what the potentials are. Duchowski (2002) surveyed how ET can be applied in visual inspection and for facilitating visual search training. The review was not limited to manufacturing, but instead provided a broad discussion of ET applications, covering also psychology, marketing, and computer science. Borgianni et al. (2018) provided an overview of how ET can be used in engineering design and assembly. Their review showed that ET can support examining the designer's behaviour and understanding cognitive work processes, and that it can facilitate the development of worker assistance systems in production. The review did not consider logistics aspects though. Our literature review differs from the previous works by discussing use cases of ET in manufacturing and logistics, with the objective to a) explore the applications of ET, b) summarize the benefits of using ET, and c) outline future research opportunities of using ET in this area. The results of our literature review support both researchers and practitioners in using ET for assisting workers in their operational activities and for improving working environments.

The remainder of this article is structured as follows: Section 2 introduces the conceptual framework used to guide the literature search and classification. Section 3 describes the research methodology used for the literature review followed by a descriptive evaluation of the sample.

Section 4 then presents the findings of the literature review, and Section 5 discusses the main insights obtained from the literature analysis and promising future research avenues. Finally, Section 6 concludes the paper with a discussion of theoretical and practical implications as well as the paper's limitations.

2. Conceptual background

2.1. Framework

Fig. 1 presents a conceptual framework that will guide the analysis of the sampled works in the subsequent sections. The framework consists of three main elements: 1) ET technology, 2) manufacturing and logistics application areas, and 3) benefits of using ET. The framework was first developed deductively based on the works of Borgianni et al. (2018) and Duchowski (2002). In this phase, possible benefits of using ET and macro application areas were determined, namely product development, production, quality inspection and logistics. The framework was then refined inductively during the examination of the literature sample. In this phase, specific application areas that belong to each macro application area were mapped. We also augmented the framework with specific benefits that may result from the use of ET for companies and humans based on the results of the literature review (see Table 3 for an overview). The different elements of the framework are described further in the following subsections.

2.2. Eye tracking technology

In general, there are two types of techniques for monitoring eye movements: a) measuring the eye position relative to the head, and b) measuring the eye orientation in space, also referred to as the "point of regard (POR)" (Young & Sheena, 1975). According to Duchowski (2017), there are four categories of methodologies for measuring eye movements, namely electro-oculography (EOG), scleral contact lens/search coil, photo-oculography (POG) or video-oculography (VOG), and video-based combined corneal reflection. The first three techniques measure eye movements relative to the head position, while the fourth can compute the POR in real time using cameras and image processing hardware. The latter techniques can also be used in interactive systems. EOG measures the skin's electric potential differences through electrodes placed around the eye (Young & Sheena, 1975). A scleral contact lens is an invasive tracker/search coil that relies on physical contact between lens and eyeball. Even though providing more accuracy in terms of eye movements, it causes discomfort at the same time (Richardson & Spivey, 2008). POG or VOG measure distinguishable features of eyes under rotation/translation, such as the pupil shape, the limit between limbus and sclera, and the corneal reflection of a closely situated directed light source by inspecting recorded eye movements (Villanueva et al., 2006). The video-based combined corneal reflection technique finally measures the reflection of a light source relative to the location of the pupil centre (Duchowski, 2017).

Initially, ET devices were highly intrusive and mostly custom-built, allowing only for short recording times with a limited number of participants (Hermens et al., 2013). In recent years, eye trackers have become commercially available, providing non-intrusive, adequately accurate and robust measurements for a range of tasks and settings (Sharma et al., 2016). Numerous manufacturers offer ET solutions today, such as Chronos vision, ASL, SR Research, SMI, or Tobii, which usually rely on video-based measurements of eye movements recorded either with a desktop- or a head-mounted setup (Bardins et al., 2008). Based on the anatomy of the human eye, three types of basic eye movements need to be modelled to localize visual attention: fixations, smooth pursuits, and saccades. *Fixations* are eye movements that stabilize over a stationary object, corresponding to one's desire to maintain the gaze on an object of interest. *Smooth pursuits* are involved when visually tracking a target in smooth motion. *Saccades* are rapid eye movements that usually take 30–80 ms and that can be executed voluntarily or reflexively (Duchowski, 2017). The most commonly used ET measures are listed in Table A1 in the Appendix.

2.3. Manufacturing and logistics application areas

This paper considers a value-creation process within a manufacturing company that starts with the development of a product, passes through production that transforms raw materials and semi-finished products into finished goods, and ends with quality inspection that ensures that the finished products meet the customers' expectations (cf. Porter, 2011). In addition to that, we consider logistics processes that make the required materials available and distribute the finished products. In the four application areas we consider, ET has been used for a number of different purposes.

In *product development*, ET was mainly used for investigating the behaviours of engineers during product design and for interpreting a customer's product perception (e.g., Borgianni et al., 2018; Mussgnug et al., 2014). In *production*, ET was primarily used for analysing workers' visual attention in performing a particular task (e.g., Amrouche et al., 2018) or to guide them in completing the task, measuring a worker's mental workload (e.g., Paletta et al., 2021), evaluating human–computer/machine interfaces and the interaction between humans and computers/machines (e.g., Walper et al., 2020), or to facilitate human–machine/robot collaboration (e.g., Berg et al., 2019). During *quality inspection*, tracking eye movements may be helpful for evaluating inspection performance (Niemann et al., 2019) and for training the visual search strategy of workers. In *logistics*, we found that ET was primarily used for evaluating couriers' interaction frequency with navigation devices during the delivery of goods (van Lopik et al., 2020) or for estimating forklift driver's mental workload during material handling and transportation activities within warehouses (Ulutas & Ozkan, 2019).

2.4. Benefits of using ET

According to Mo (2012), Prodan et al. (2015), and Tobii Pro (2022), ET can lead to improvements in process performance, human performance, and work environment and safety. As ET is a valuable tool for monitoring eye movements of workers and detecting process consistencies for a wide variety of manufacturing and logistics activities, our review aims to synthesize the benefits of ET, such as productivity and inspection performance improvements. According to the eye-mind hypothesis, eye movements reflect the attention process of humans (Just & Carpenter, 1976). Since ET enables observing and recording human visual behaviour during task fulfilment and decision making, ET can help identify best practice methods adopted by humans, and enhance human performance in terms of knowledge and skill improvement. Humans are involved in their working environment and interact with colleagues, machines, or robots. Risks may occur when there is a lack of situational awareness. In this regard, ET may help monitor worker's visual attention and identify potential hazards, which helps to improve workplace design for a safer working environment.

3. Methodology

3.1. Literature search and selection strategy

Systematic literature reviews aim to identify, evaluate and synthesize research on a particular (set of) question(s) to identify and potentially fill research gaps and strengthen the field of study (Petticrew & Roberts, 2006). This paper aims to collect and analyse the literature on the application of ET in manufacturing and logistics. We adopt the systematic review and meta-analysis (PRISMA) approach (Page et al., 2021) used by, among others, Winkelhaus et al. (2021) and Füchtenhans et al. (2021).

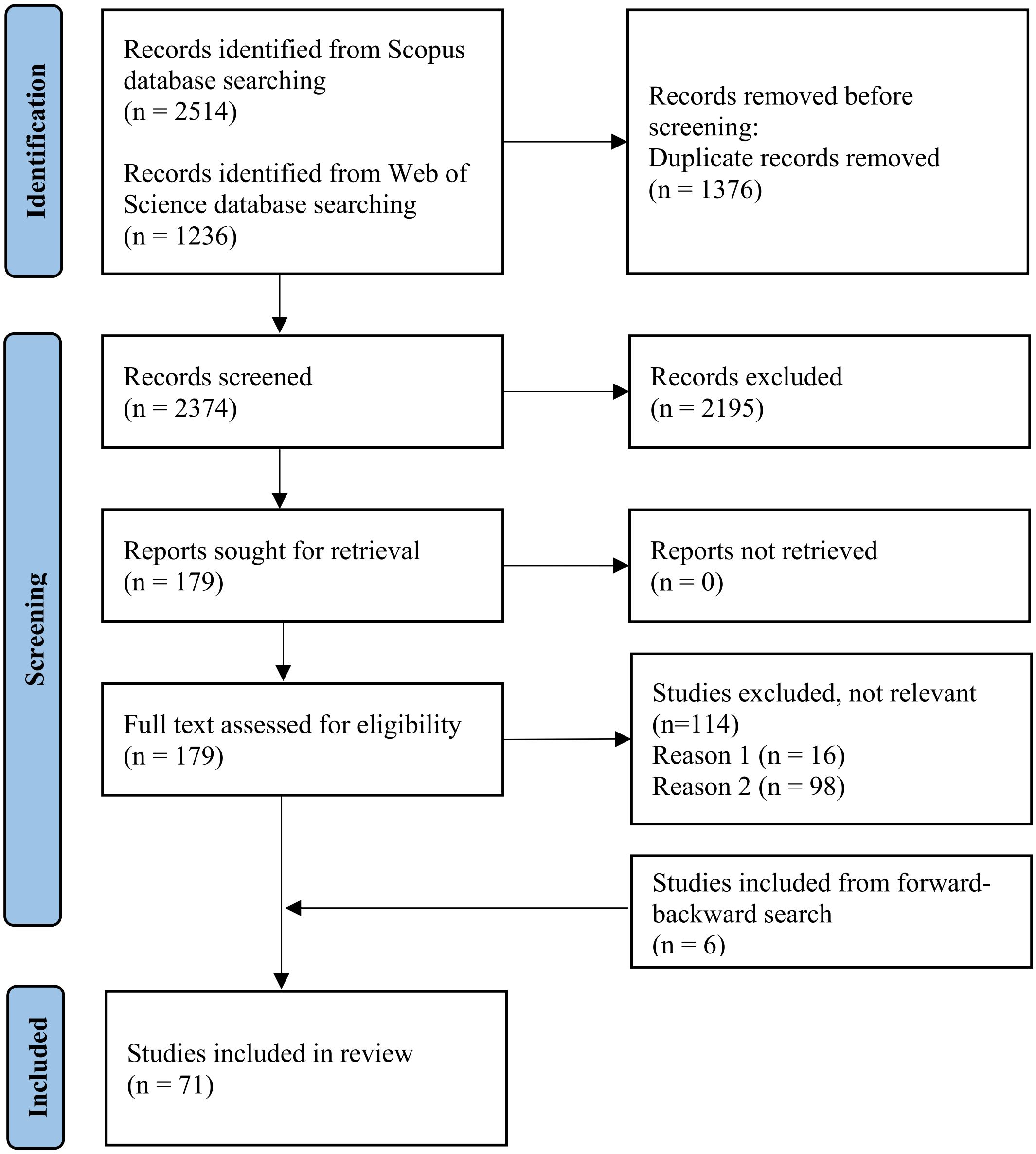

Fig. 2. Literature selection flow diagram based on the PRISMA approach.

Our literature search and selection strategy, illustrated in Fig. 2, consisted of three main steps: (a) define relevant keywords, (b) search two scholarly databases, and (c) identify relevant papers.

Two groups of keywords were established based on the framework described in Section 2. The first set of keywords is related to ET (eye-track* OR "eye track*"); the second set of keywords was selected according to the context where ET is applied, in our case manufacturing and logistics ("product development" OR "product design" OR "engineering design" OR manufacturing OR production OR operations OR "industrial engineering" OR "quality inspection" OR "quality control" OR "quality check" OR logistics OR warehous* OR distribution OR delivery). All keywords contained in the first group were combined with all keywords from the second group to generate the final keyword list by using the Boolean operator 'AND'. The keywords were used to search two databases, namely Scopus and Web of Science (WoS). Works that appeared until December 2021 and that feature at least one of the keywords in the article title, abstract, or list of keywords were retrieved for further analysis. Only papers that were published in scientific journals or conference proceedings in English were kept in the sample. We included conference papers because researchers have just recently started to apply ET in manufacturing and logistics, and in many cases, technological innovations are discussed in conference proceedings first (see also Glock et al., 2021). The initial literature sample consisted of 3750 papers from Scopus and WoS. After removing duplicates, 2374 papers remained in the initial sample.

In the second step, we first screened the papers' titles, abstracts, keywords and dissemination outlets. The following selection criteria were applied: selected papers need to 1) present research related to manufacturing and logistics, and 2) report the results of an ET application. The selected papers were catalogued in an Excel spreadsheet identifying the area and/or process where ET is applied. Papers that satisfied the criteria were added to a refined list of papers for analysis. In this stage, all authors were involved to cope with selection bias, and a shared Excel worksheet was used to support and track the entire history of article filtering, screening, and coding. Any mismatch in the decisions was thoroughly discussed and reviewed among the authors. Then the screened papers were exported to Mendeley© Reference Manager for full text reading, and only papers that examined ET and provide useful insights about ET potentials in manufacturing and logistics remained in the sample. Papers were removed if 1) ET was not the focus of the paper,

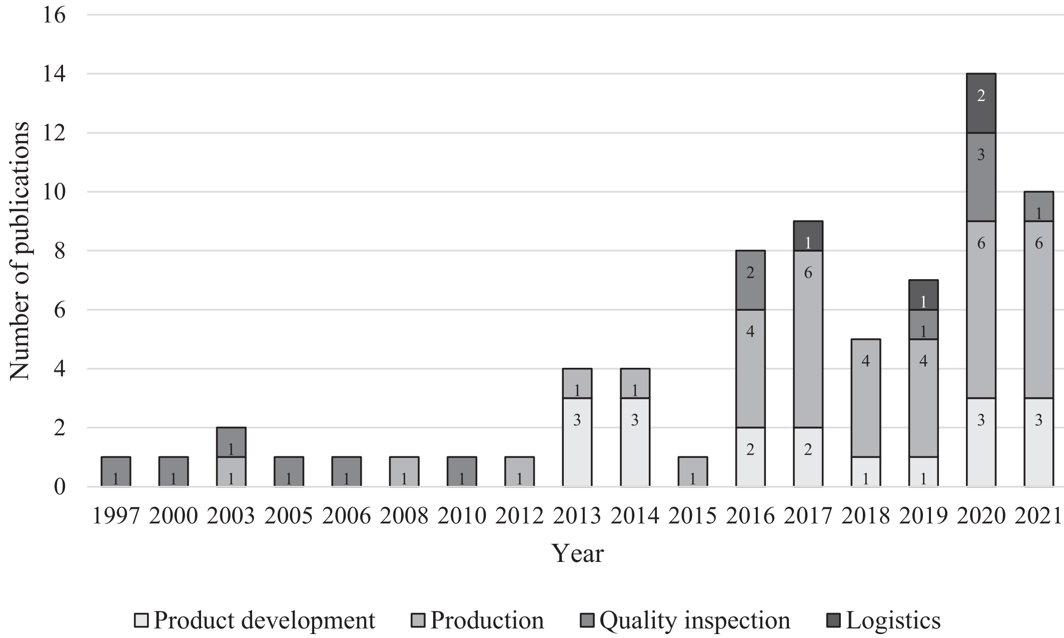

Fig. 3. Number of publications over time and per application area.

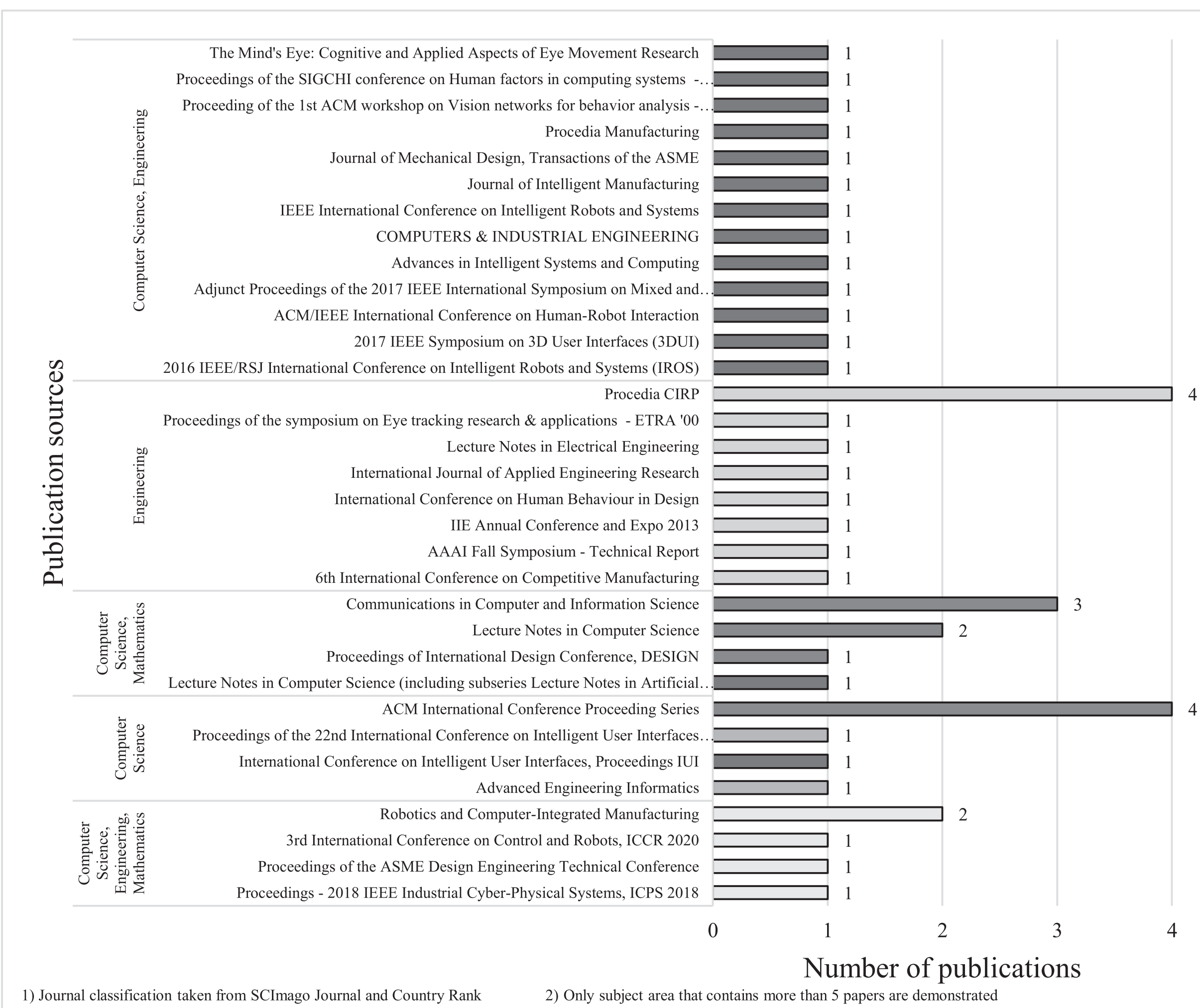

Fig. 4. Number of publications per outlet.

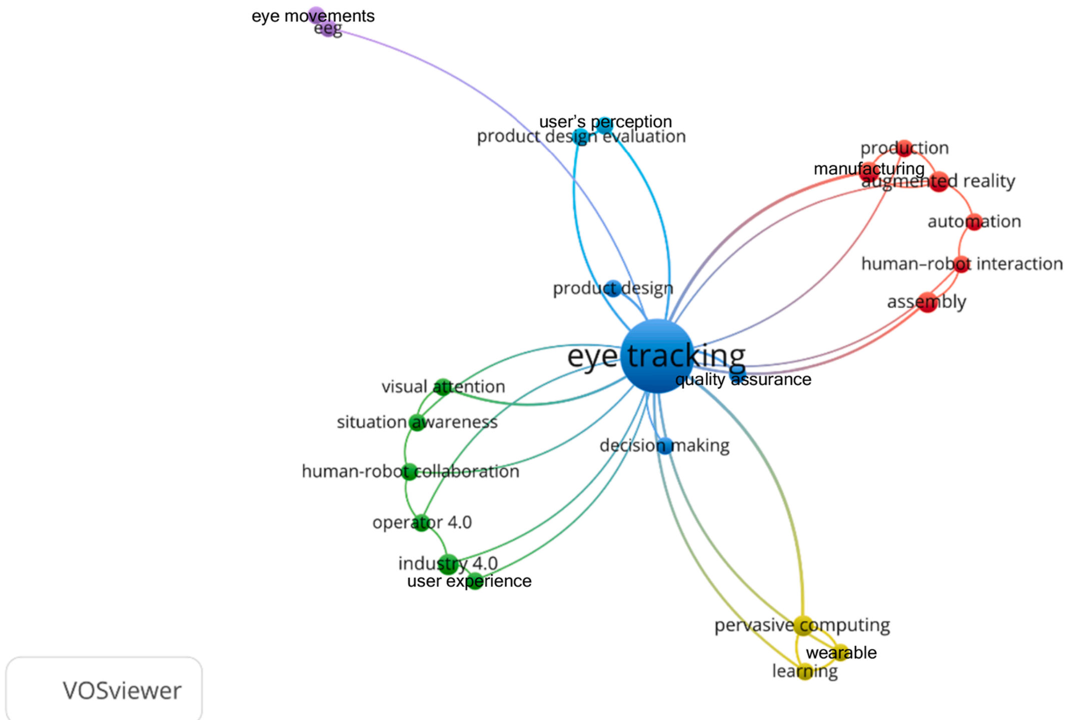

Fig. 5. Co-occurrence network of author-provided keywords contained in the literature sample.

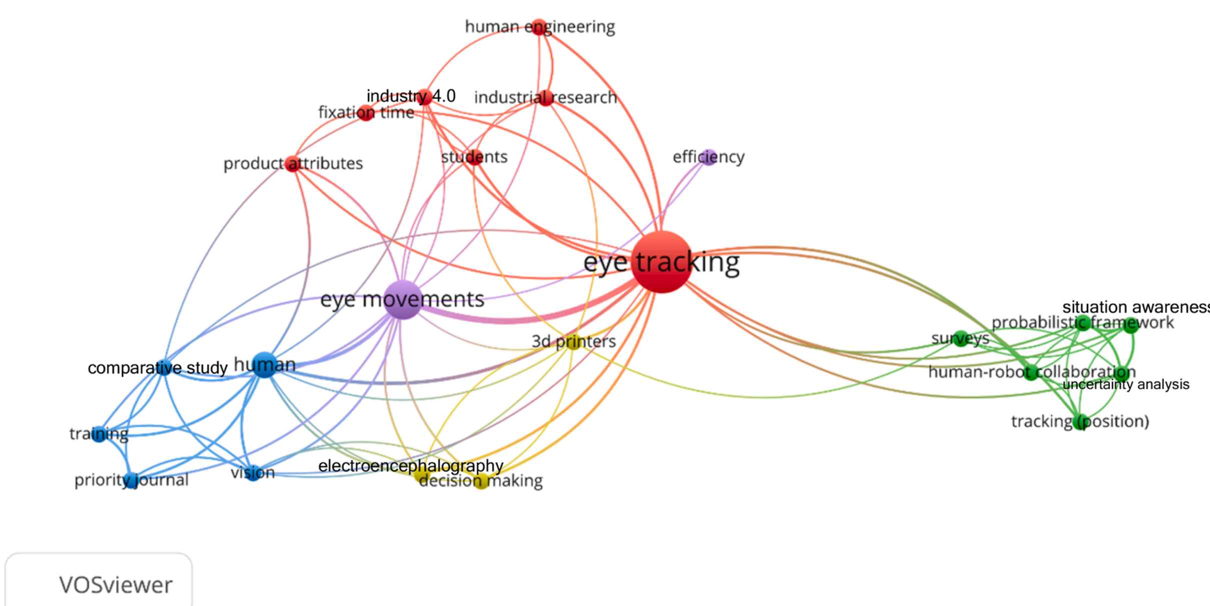

Fig. 6. Co-occurrence network of indexed keywords for the literature sample.

or 2) no insights related to manufacturing and logistics were reported. This selection process identified 65 papers suitable for final review. In addition, a forward–backward search (during which we checked both the reference lists of the sampled papers and works citing the sampled papers for possible relevance) was performed to overcome possible keyword search limitations. This step added six papers to the final review sample, leading to a total sample size of 71 papers.

3.2. Descriptive analysis

This section descriptively evaluates the 71 papers identified during the literature search in terms of a) publications over time, b) important publication outlets, c) co-occurrence network of keywords, d) research methods used, and e) types of ET equipment employed. Fig. 3 depicts the number of papers published per year. As can be seen, researchers have been working on ET in manufacturing and logistics for more than two decades, with a strong increase in publication numbers in recent years. More than 70% of the sampled papers were published from 2016 onwards, indicating that the interest of academics in exploring ET applications in this domain increased just recently. This may be the result of technological progress in ET, with more and more technology providers offering ET devices that enable an accurate measurement of eye

Table 1
Research methods used in the sampled ET studies.

Research method		Number	Percentage
Quantitative method	Experiment	25	35.2%
Total		25	35.2%
Mixed method	Experiment and survey	28	39.4%
	Experiment and simulation	3	4.2%
	Experiment and data analysis	3	4.2%
	Experiment and analytical model	2	2.8%
	Experiment and qualitative study	1	1.4%
	Experiment, simulation, and data analysis	3	4.2%
	Experiment, survey, and qualitative study	2	2.8%
	Experiment, survey, and analytical model	1	1.4%
	Experiment, survey, and data analysis	1	1.4%
	Experiment, survey, qualitative study, and analytical model	1	1.4%
	Experiment, survey, qualitative study, and simulation	1	1.4%
Total		46	64.8%
Overall		71	100%
Experimental setting		**Number**	**Percentage**
In the lab		56	78.9%
In the field		15	21.1%
Total		71	100%

Table 2
Types of eye tracking devices.

ET equipment type	Number	Percentage
Desktop-based ET	22	31.0%
Mobile ET	46	64.8%
Desktop-based and mobile ET	1	1.4%
Webcam ET	2	2.8%
Total	71	100%

movements. Concerning the publication outlets, the sampled articles were published in a broad variety of interdisciplinary journals and conference proceedings (Fig. 4). Figs. 5 and 6 show the co-occurrence networks of author-provided keywords and indexed keywords separately by using VOSviewer software (Van Eck & Waltman, 2022). The cluster of keywords identifies sets of keywords that appear most often together in the papers, where different clusters are represented by different colours. The occurrence of the nodes (which represent keywords in our case) are represented by circles with different dimensions. We only considered author keywords that appeared at least twice, and identified six clusters composed of 23 nodes (Fig. 5). For the indexed keywords, we only considered keywords that appeared at least three times, and identified five clusters composed of 22 nodes (Fig. 6). The keywords co-occurrence networks show that ET studies deal with a variety of applications (e.g., product design evaluation, human robot collaboration, quality assurance), and address different human-related issues (e.g., perception, decision making, learning, situation awareness).

Table 1 shows the research methods that were adopted in the sampled ET studies and gives an overview of the settings in which the studies were conducted. Our literature sample has a strong experimental orientation: 25 of the sampled papers conducted ET experiments, and the rest combined ET experiments with other methods, including surveys (statistical analyses of collected factual data from questionnaires), qualitative studies (investigations of phenomena within their real-life context and data collections from participant observations, semi-structured interviews, and focus groups), analytical models (mathematical modelling, optimisation models), simulation (experiments on the reaction of a model, software programs and techniques), and data analyses (analyses of existing data) (Busetto et al., 2020; Glock et al., 2017). This strong experimental character is due to the nature of ET, which is a technology that is well suited for data collection in experiments. In mixed-method approaches, most of the ET studies combined experiments with surveys to increase the validity of the results. Table 2 also shows that ET experiments were predominantly carried out in laboratory settings. 15 works conducted field studies, implying that recent technological advances also enable field investigations. Table 2 gives an overview of the type of ET devices used. Our results show that mobile ET equipment enjoyed a higher popularity than desktop-based equipment. One possible explanation is that our literature sample investigates manufacturing- and logistics-related tasks where workers often change their position over time, such that mobile ET solutions are required to enable the workers to complete tasks realistically (Meißner &

Table 3
Benefits of using ET in manufacturing and logistics.

	Process performance	Human performance	Work environment and safety
Product development	• Evaluate and improve product design (ID: 1, 2, 4, 5, 7, 9, 10) Improve engineering design communication (ID: 15)	• Facilitate novice training (ID: 13)	–
Production	• Identify activities for improvement (ID: 19, 22) Improve human–computer/machine communication efficiency (ID: 36, 37, 39, 43, 45, 46)Improve human robot interactive efficiency (ID: 48)	• Facilitate novice training (ID: 21, 22, 24, 29)	• Improve workplace design (ID: 33, 34)Detect deficiencies in concentration and mental overload (ID: 30, 31, 32)
Quality inspection	• Improve quality inspection efficiency (ID: 55, 56, 57, 58, 62, 64, 65, 66, 67)	• Facilitate novice training (ID: 58, 62, 64, 65, 66, 67)	• Improve workplace design (ID: 55, 56)Detect cognitive hacking (ID: 61)
Logistics	• Improve human robot communication ergonomics (ID: 71)	–	• Improve delivery safety (ID: 68)Improve occupational safety (ID: 70)Improve human robot interaction safety (ID: 71)

Oll, 2019). We also noted that a broad variety of ET solutions were used in the sampled papers, which enables researchers to benefit from the various advantages different types of equipment offer. Tobii and SMI were found to be the most popular providers of ET solutions in our sample.

4. Results of the literature review

The analysis of the selected papers is structured along the framework shown in Fig. 1. An overview and categorization of the 71 sampled papers are provided in Table A2 in the Appendix.

4.1. Product development

4.1.1. Interpreting the customer's product perception

Research has shown that ET helps interpret how customers perceive a product, which can be considered in the improvement of product designs. Li et al. (2018) used ET to quantify subjects' interest in a product. Their results showed that the product classified by customers as the most preferable received the most fixations; fixations could hence be seen as a proxy for the customer's interest in a product. Du and MacDonald (2014) investigated whether ET can predict the relative importance of product features, and whether it can be used to identify by how much a particular product feature needs to change to be noticeable by a customer. The authors found positive correlations between product feature importance and three types of gaze data (fixation time, percentage fixation time, fixation count) and a negative correlation between feature importance and first-located time. Borgianni et al. (2019) investigated how customers perceive products created by additive and traditional manufacturing processes. The authors combined a self-statement questionnaire with ET and found that the questionnaire should be used to measure perceived attractiveness, quality and representation of the product, while ET should be used to assess exploration, impact and attention attributes of the product. Kuo et al. (2021) explored the use of ET for the interpretation of users' emotions on product design. Their results show that users' eye movements correspond to their impression of the product. Moreover, both experts' and novices' visual attention are driven by the most attractive component of the product. Both Borgianni et al. (2019) and Kuo et al. (2021) argued that ET should not substitute questionnaires or interviews, but instead be used in parallel to extract phenomena that are difficult to capture via self-statement questionnaires. Yang et al. (2021) used ET to verify whether products with emotional design factors influence the user's visual behaviour. They concluded that pupil diameter can be used as an indicator of the emotional arousal of the user.

Beyond interpreting the user's perception of a product, ET may connect user responses and the design intent of designers. The studies of Purucker et al. (2014) and Hyun et al. (2017) showed that the probability of a user looking at a product depends on different design elements, and therefore, potential design changes can be evaluated with the help of ET. Yang et al. (2016) used ET complemented by gesture recognition to investigate how users understand a product by analysing the users' visual and motion behaviours. They concluded that combining these two techniques can effectively capture user intent and guide product design. Li et al. (2017) combined electroencephalography (EEG) and ET technology to record both brain activity and gaze. In this setting, EEG measures the subject's excitement level and ET records the subject's fixation points. The results of the study indicate that processing both types of data in a fuzzy logic model gives a good estimate of the subject's product preferences. According to Wang et al. (2020), using data collected from ET and EEG can predict subjects' product design preferences, and combing ET and EEG data can achieve best prediction accuracy. Moreover, Schmitt et al. (2014) showed that ET and bio-signals (electromyography – EMG, galvanic skin response – GSR) can indicate the importance of product attributes as perceived by the customer.

4.1.2. Investigating the design process

In addition to measuring user perception of product attributes, ET may also provide insights into human behaviours while working with blueprints, diagrams, and manufacturing design guidelines. Matthiesen et al. (2013) used ET to detect the cognitive behaviours of engineers while they build up a functional understanding of a technical system with different representations (2D or 3D drawings or the physical object). Their results show that gaze data may provide information that cannot be captured from audio and video data, thus complementing other empirical methods (e.g., document analysis, interviews, or protocol analyses). ET was also found to be less intrusive than other empirical methods. Nambiar et al. (2013) used ET coupled with a retrospective think-aloud protocol to analyse the visualization strategies adopted by experts during the reading of blueprints of mechanical parts. The authors grounded their analysis on data/frame theory to list the experts' concrete activities and identify task priorities. The results were used to formulate a cognitive map that describes the expert's blueprint reading process, which facilitates novice training. Nelius et al. (2020) used ET to investigate how design engineers are influenced by confirmation bias (i.e., the tendency to seek and interpret information in a way that corresponds to one's own view). They found that confirmation bias is associated with short fixation time, and that it has a negative impact on reasoning during analysis in engineering design.

Maier et al. (2014) used ET to investigate whether the unified modeling language (UML) layout has an impact on UML diagram comprehension. They found that compared to both objective measurements (time, accuracy) and subjective assessments (difficulty, effort), the ET measures cannot clearly indicate that a large diagram size or a low diagram quality lead to low performance and/or high cognitive load in diagram comprehension. The authors argued, however, that diagram understanding involves various mental processes that require further research to improve the predictive power of ET analyses. Boa and Hicks (2016) explored the information operation process (finding, familiarisation, comprehension, review critique and review selection) of engineers via ET by measuring the saccade amplitude fixation duration ratio (SF ratio). Their results showed that the overall distribution of SF ratio for individual information operation processes is higher than for the baseline activity of reading, implying a more ambient processing for information operation processes. They also found that the SF ratio depends on the stimuli scene (symbolic or iconic information), where iconic information interaction is more aligned with ambient processing while symbolic information interaction is more aligned with focal processing.

To investigate the interaction between subjects and manufacturing design guidelines, Doellken et al. (2021) introduced gaze entropy to indicate how "disordered" the visual behaviour of a subject is. Their results showed that engineers and students demonstrate different visual behaviours. High-performing engineers tend to focus their visual attention with less switching behaviour, while high-performing students exhibited a more exploratory behaviour. Mehta et al. (2020) finally used ET to understand the cognitive processes of designers during redesign for additive manufacturing (AM). Their results showed that high-performing designers spend much more time on indirect design activities, such as stress analysis, than low-performing designers.

4.2. Production

4.2.1. Work analysis and task guidance

Compared to the traditional recognition of human activities via cameras, ET enables a more precise monitoring of human attention. In production, ET can be used to monitor the quality of task execution and for evaluating workers' skills and performance. Bhatia et al. (2015) explored the relationship between visual distance and human task performance for a manual precision task. They observed that in standing posture, the participant visualizes the complete workspace in a narrow visual field of view, and as a result, the visual estimation of the target location and hand trajectory become faster. Their results imply that within a permissible range of visual distances, the longer the visual working distance, the quicker the task completion time with fewer eye fixations of the task. Shotton and Kim (2021) used ET to assess workers' attention levels during assembly tasks, and found that the attention level can influence the workers' visual fixations of tasks. Amrouche et al. (2018) used ET to capture changes in workers' visual attention in real time and to map it to the execution of semi-manual industrial assembly tasks. The authors found that the change of the nearest neighbour index (NNI) is correlated with task switching, and concluded that NNI values can be used to detect the onset and offset of activities. Haslgrübler et al. (2019) studied the relationship between eye-hand coordination and fine and gross motor skills required for completing a task. They concluded that eye-hand coordination patterns are correlated with the skill set required to complete the task, and that eye-hand coordination can therefore be used to explain the movement precision during task completion. Manns et al. (2021) proposed a motion capture system that combines ET with body motion and hand tracking to identify worker's activities and predict worker's actions in manual assembly. Bovo et al. (2020) studied the use of hand signals only, gaze signals only, and joint hand and gaze signals for tracking working tasks and for inferring the worker's intention. Their results showed that combined hand and gaze data leads to the best performance in inferring the worker's intention, while hand data only leads to the best performance in tracking working tasks.

Bovo et al. (2020) also showed that prediction errors can be reduced if hand and gaze tracking is complemented by augmented reality (AR). ET can indeed be combined with AR to support manufacturing tasks (Sausman et al., 2012), for instance, to capture the user's focus and to compare it with typical operations scenarios to identify possible gaps in the viewer's perception and to guide the user through AR (Ivaschenko et al., 2018). Renner and Pfeiffer (2017b,c) compared a new AR-based spherical wave guidance technique with arrow guidance, attention funnel guidance, and the stationary display of an image on the screen. Their objective was to investigate which guidance technique leads to the best task performance in a virtual reality (VR) environment, wherein ET was embedded in an AR device to monitor the participant's gaze direction and modulate its feedback accordingly. Their results show that equipping an AR device with ET can slightly reduce head movements and task completion time, and that ET is particularly helpful when the gaze of the participant is outside of the AR display.

The recognition of activities via ET also facilitates the training of novices. If an ET-based system is able to identify the different steps of an assembly task, for example, then the system can provide supervision with respect to the correct or incorrect execution of the task (Amrouche et al., 2018; Bovo et al., 2020). Given that eye-hand coordination patterns can explain the movement precision during task execution, ET can efficiently support training on the job and help to identify a point in time when the novice shows a consistent performance to indicate the completion of the training (Haslgrübler et al., 2019). Another attempt to adopt ET for novice training in an assembly context was made by Haslgrübler et al. (2018), who explored how different instructional video formats impact training efficiency. The authors did, however, not find clear evidence that instructional videos with gaze annotations are better than first-person and third-person view videos.

4.2.2. Evaluating mental workload

Mental workload reflects the mental strain on a worker that results from performing a task under specific environmental and operational conditions (Cain, 2004). Measuring mental workload is challenging in real-world working situations, as traditional measures (such as the NASA-TLX) are subjective and often too intrusive. ET, in this regard, provides a non-invasive option for gathering attentional information and measuring mental workload. Nandakumar et al. (2014), for example, proposed a method based on ET combined with the MATLAB wavelet toolbox to estimate cognitive workload and compared this measure to the Index of Cognitive Activity. Their results showed that a bigger pupil diameter indicates a higher mental workload. The authors suggested monitoring the pupil status of workers in real time to track the mental alertness level of the workers and to guarantee safe operations in the plant. Straeter (2020) combined ET with the pupil graphic sleepiness test (PST) to detect mental fatigue in monotone and repetitive manufacturing tasks. They observed that mental fatigue, measured by evaluating the variance of the pupil diameter, is correlated with the monotony effect.

Paletta et al. (2021) presented a novel method for measuring both cognitive load and biomechanical strain. Their method uses ET to analyse eye movements during task execution and wearable sensors to analyse sensorimotor patterns of workers. Instead of analysing the pupil diameter, they developed a heuristic concentration indicator using gaze-referenced regions-of-interest data to estimate mental workload. They concluded that working continuously for more than 20–30 min with high concentration increases mental fatigue, which, in turn, intensifies risk factors at work. Peruzzini et al. (2017) and Peruzzini et al. (2020) proposed a new protocol that incorporates ET, multi-parametric wearable sensors (heart rate, breathing rate, skin temperature, posture angle), a video camera, digital modelling, and a subjective questionnaire to assess physical ergonomics and mental workload of workers. The authors suggested to use biometric and ET measures together with the NASA-TLX questionnaire to evaluate mental workload.

Van Acker et al. (2021) finally explored concrete changes in assembly behaviours as indicators for mental workload variations by observing and analysing recorded ET videos. The authors developed a coding scheme for assembly behaviour and tested it under high- and low-complex assembly conditions. They found that behaviours such as 'parts collection', 'positioning', 'part rotation', 'positioning attempt' and 'freezing' were significantly higher in occurrence and/or duration during the execution of highly complex assembly tasks, as compared to low-complex tasks, revealing high mental workload.

4.2.3. Assessing human–computer/machine interfaces and interaction

Humans and machines can communicate with each other via various user interfaces including visual displays, hand and face gestures, speech and non-speech audio for alerts and physical interaction and haptics (Goodrich & Schultz, 2007). ET, in this regard, provides opportunities to assess human–computer/machine interface usability to improve communication ergonomics. Zülch and Stowasser (2003) used ET to explore visual strategies adopted by subjects during their interaction with shop floor scheduling software and investigated the relationships between different data representation forms (e.g., alphanumerical vs. symbolic coding) and the data interpretation patterns of the subjects. Their results show that ET can identify a subject's visual strategy and detect the subject's preferences regarding different data representation forms, which facilitates a user-friendly interface design.

Using ET combined with a questionnaire, Wu et al. (2016) found that the complexity of LED interfaces used in manufacturing significantly affects users' visual attention and feelings. The authors concluded that ET combined with a questionnaire can help to effectively evaluate the usability of a human–machine interface. Wu et al. (2016) and Walper et al. (2020) used ET to investigate the effect of user experience on the user's interaction with different interface designs. Wu et al. (2016) showed that when the interface complexity increases, novice users become less efficient in searching for information. Therefore, a simple interface design is recommended for this user group. Walper et al. (2020) found that experienced users spend less time on working with an interface and that they dedicate more time to off-screen task processing. Zhang et al. (2017) used ET to evaluate and improve the design properties of a CNC machine tool interface. By analysing the user's visual behaviour, they developed a user-friendly interface that enhances the interactive experience of the workers.

Apart from assessing the usability of human–computer/machine interfaces, ET was also applied in evaluating the effectiveness of instructive information in production. Lušić et al. (2016) compared the influence of static (picture-based) and dynamic (animated) instructions for manual assembly tasks and used ET to capture the real view of the workers during their interaction with the medium providing the information and the assembly objects. They found that workers complete assembly tasks faster with a lower lookup frequency when dynamic instruction is provided. Heinz et al. (2020) used ET to analyse how users access the assembly instruction shown on a digital projection-based assistive system and found that users tend to have lower non-linear viewing sequences in a repeated assembly task, and that learning effects exist in the use of the assistive system. Tang et al. (2019) investigated a robot signalling solution within a collaborative human-robot assembly system. They proposed the Robot Light Skin (RLS) concept as a visual indication system that communicates the robot's status to the workers. Using ET and semi-structured interviews, they showed that the RLS concept performs better than a traditional tower light solution, as workers have less fixations on the RLS compared to the traditional system during their assembly task. The workers were also shown to react faster and perform more tasks when the RLS concept was adopted.

Other works investigated the role of ET in interactive visual control in production. Bardins et al. (2008) combined ET and head tracking to estimate gaze-in-space to enable a gaze-based control of the assembly workbench interface. They also conducted usability studies and confirmed that the user can interact with the graphical user interface quickly and intuitively through the proposed gaze-driven interaction system without getting distracted from a parallel manual assembly task. Jungwirth et al. (2018) compared an ET approach with physical hand operations for the remote interactive control of devices during task completion. Their results showed that the gaze-based approach has advantage in controlling distant devices, and that physical control performs better in case of short distances. The authors also concluded that gaze-based interactive control is particularly helpful for workers in adjusting machine settings when their hands are occupied.

Guo et al. (2013) developed a prototype to infer the user's intent for matching assembly parts in a virtual assembly environment. Their results show that it is possible to realize interactive gaze control for virtual assembly. A similar attempt was made by Zhao et al. (2021), who utilized ET and hand tracking data as input for the control and movement of robots in a virtual assembly environment through a computer interface. The authors further compared the eye-hand interaction mode with a touch screen and found that eye-hand control leads to shorter assembly task completion time than traditional interaction. Li et al. (2021) also illustrated the possibility of using ET for interactive visual control. They proposed a human–computer interaction framework that contains a target recognition and a target capture module to enable the interaction with the robotic grasping system by directly gazing at the object of interest.

4.2.4. Facilitating human–machine/robot collaboration

ET also enables a seamless collaboration between humans and machines/robots, especially in terms of interpreting human intention and enhancing workers' SA in a collaborative working environment. According to Palinko et al. (2016), eye gaze alone carries sufficient information to enable the robot to interpret human intention. The authors developed an ET system that tracks gaze position based on an estimation of head orientation and face features and compared it with a pure tracking of the head position in a human-robot collaborative task. Their results show that ET enables the robot to complete the task with a higher success rate and a lower completion time compared to using head position alone. A questionnaire-based evaluation also suggested that the participants prefer the ET system when they interact with the robot for the collaborative task.

Admoni and Srinivasa (2016) argued that ET provides an additional implicit signal to help predict the user's goals. They proposed an approach that integrates eye gaze into a Partially Observable Markov Decision Process model based on the idea that task-based gaze is primarily focused on the task before the hand starts moving towards it. The proposed approach was validated in an initial experiment, showing that gaze-based interaction has great potential in a shared autonomy interaction scenario. Fan et al. (2020) proposed a novel approach that takes gaze signal and spatial information as inputs for the assistive control of Supernumerary Robotic Limbs (SRL). Their results show that SRL operations controlled by gaze can assist workers without interrupting the current work process, and that it takes the SRL solution only 0.2 s to execute after the worker stares at the task. Berg et al. (2019) investigated the interaction between humans and an industrial mobile robot based on human gestures and eye movements. Output information was displayed using a pocket projector. Their results demonstrate the feasibility of using intuitive input (eye gaze and gestures) for establishing a mutual communication between humans and robots.

Apart from controlling robots, ET can also be used to evaluate SA, which involves a situational understanding and a projection of future system states in light of the worker's pertinent goals as a basis for decision making (Endsley, 1995; Lundberg, 2015). Paletta et al. (2017) proposed a novel approach that combines ET and motion tracking to estimate the SA in human-robot interaction. The authors developed a probabilistic measure of distance between the worker's gaze and an object's volume of interest and introduced 3D-NNI to characterise the user's visual distribution with respect to objects of interest. They compared the ET approach with traditional SA measurement methods, such as the Situation Awareness Global Assessment Technique (SAGAT) and the Situational Awareness Rating Technique (SART), and confirmed that an ET-based estimation of SA is correlated with SAGAT and SART results. Thus, measuring the worker's gaze through ET can serve as a solid basis for predicting SA (Dini et al., 2017; Paletta et al., 2019).

4.3. Quality inspection

4.3.1. Investigating quality inspection patterns

Visual inspection is important in manufacturing. Tracking eye movements during visual inspection enables the detection of eye movement patterns, which can be used for improving inspection performance (Duchowski, 2002). Schlösser et al. (2016) and Niemann et al. (2019) combined ET with a questionnaire to analyse the worker's visual inspection patterns with the objective of optimizing quality control at a

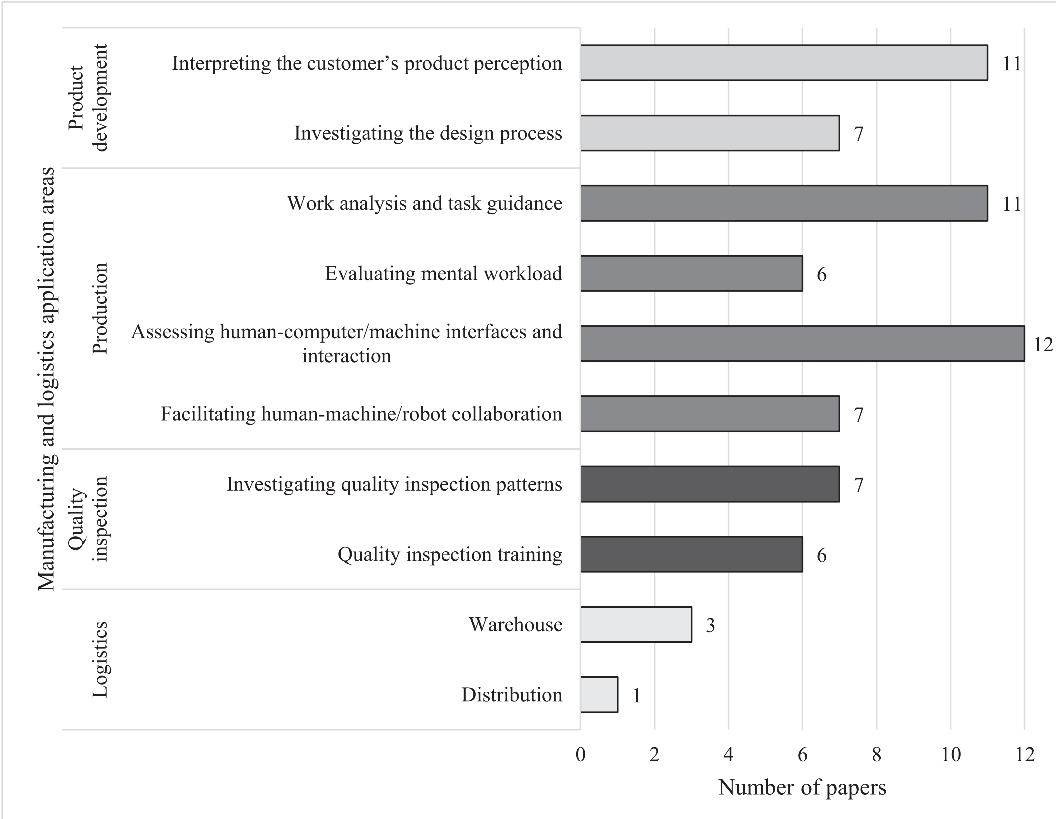

Fig. 7. ET applications in the manufacturing and logistics literature.

Table 4
Typical ET measures used.

Manufacturing and logistics application areas	ET use	Selected main ET measures
Product development	Interpreting customer product preferences	Fixation duration, number of fixations First fixation time, first fixation points
	Investigating the design process	Fixation duration, SF ratio, gaze entropy
Production	Work analysis and task guidance	Position of fixations
	Evaluating mental workload	Pupil diameter
	Assessing human–computer/machine interfaces and interaction	Time to first fixation, fixation duration, dwell time, position of fixations
	Human-machine/robot collaboration	Position of fixations
Quality inspection	Investigating quality inspection patterns	Position of fixations, fixation duration, scanpaths
	Quality inspection training	Position of fixations, fixation duration, scanpaths
Logistics	Warehouse and distribution	Number of fixations, fixation duration

paint shop in automotive manufacturing. The authors found that the workers' actual visual movements differed from given work instructions, and that some critical parts were not fixated long enough for quality control. The questionnaire revealed that workers' eyes got tired after half of the working hours, and that 40% of the workers could not sufficiently concentrate on their tasks after five hours of working. Based on these findings, the authors suggested to compare actual work processes regularly with standardized work sheets, to adapt processes if necessary, and to improve light conditions in the working environment.

Tuncer et al. (2020) used ET to improve the efficiency of in-line inspection processes and assembly line balancing. They argued that ET can quantitatively measure workers' inspection locations and inspection times for each task, and as a result, the balancing of the assembly line can be optimized by eliminating inconsistencies between anticipated and actual task execution time. Ozkan and Ulutas (2016) compared the quality inspection patterns of novices and experienced workers in ceramic tile manufacturing using ET, and found that experienced workers fixate more on the inspected objects than novice workers. Similarly, Ulutas et al. (2020) examined the visual attention patterns of novices and experienced workers by combining ET with Hidden Markov Models. Their results show that experienced workers use a thorough and systematic inspection strategy and that they are capable of inspecting all predetermined important areas, while novice workers tend to make a general view of the inspected object and ignore some areas that should have been inspected.

Aust et al. (2021) examined the relationship between product cleanliness and the inspection performance of aircraft engine blades, where ET was used to identify search strategies adopted by groups of subjects with various levels of expertise. The results show that ET can directly detect search errors by evaluating (a lack of) fixations on the defective area, but that it can detect recognition errors (where the defective region is fixated, but where it is not recognised as relevant for the further decision-making processes) only when complemented by additional evidence (e.g., defect marking on the inspected image). They also found that more experienced subjects tend towards a more systematic search for the defect with a lower inspection time regardless of cleanliness of the inspected object; when the inspected object is dirty, however, the inspection accuracy decreases for all subjects.

ET also helps to reveal changes in visual attention when cyber vulnerabilities are introduced during quality inspection. Huang et al. (2020) combined EEG sensors and ET to detect cognitive hacking of workers in a computer aided quality inspection setting, where participants are required to inspect the surface roughness of AM components. Subliminal primes were introduced into the human machine interface for data-logging to mislead inspection without being directly perceptible. The results reveal that participants showed different cortical and eye movement behaviours when priming was present, and that EEG and ET are useful in detecting cognitive hacking.

4.3.2. Quality inspection training

Also in quality inspection, ET enables improved training strategies. Wang et al. (1997) investigated if the visual search strategy can be changed by training. The authors used ET to monitor the subject's eye movement patterns and trained three groups of participants with different search strategies (systematic, natural, random) for the inspection of printed circuit boards. They found that through monitoring the participants' eye movements and providing performance feedback, the participants' visual search strategies could be trained. Duchowski et al. (2000) developed a VR simulator with a binocular eye tracker built into the head mounted display. Their objective was the training of workers' inspection skills in an immersive virtual environment. Sadasivan et al. (2005) also studied if the search strategy can be trained using a feedforward training display that shows ET information gathered from an expert inspector. They found that ET can capture the expert's cognitive process during inspection reflected in the chosen search sequences. Novices can then improve their inspection efficiency through scanpaths-based feedforward training. The authors also used a questionnaire to evaluate the usefulness of scanpaths-based training, and found that participants consider the expert's search strategy valuable in improving their own inspection performance.

Bowling (2010) investigated the relationship between the amount of feedforward information (FI) provided to a subject and the subject's visual behaviour. They tested four levels of FI (without FI, FI pertaining to severity of damage, FI pertaining to severity and probability of occurrence of damage, FI pertaining to severity, probability of occurrence and location of damage) and found that providing more FI causes the search process of trained participants to become more systematic, i.e., it displays a greater number of focus groups, a shorter mean fixation duration, and a broader covered area. Nalanagula et al. (2006) used ET to record an expert inspector's search strategy, and created three display types, namely a static (a static image which shows the scanpaths of the expert), a dynamic (a cursor that moves across the inspected object and represents the sequential eye movement of the expert), and a hybrid (similar to the dynamic display, but it also leaves a static trace as the cursor moves along to display) one, to investigate which kind of display technique is more effective for training novice inspectors. Their results confirm Bowling (2010), showing that FI helps training groups to adopt a more systematic search strategy compared to groups that did not receive FI. In addition, the group that was trained via the hybrid display achieved the highest search performance.

Nickles et al. (2003) tried to verify how different training modes (verbal instruction only, verbal instruction and a static diagram, and verbal instruction together with a static diagram and dynamic training aid) impact workers' visual inspection search, where ET was used to monitor the visual behaviour of trained novices. The authors found that novices improved their inspection performance with fewer fixations on inspected objects after training. However, there was no significant difference between the different instruction modes in terms of performance and eye movement features. The authors therefore recommended verbal instruction as the preferred training method in practice as it is the least complex to implement.

4.4. Logistics

Papers that discuss ET applications in logistics are rare; only four papers were found that investigate ET in this domain with a focus on distribution and warehousing activities.

Using a navigation device could help a courier to successfully deliver a product whilst maintaining SA to avoid potential hazards. In this regard, Van Lopik et al. (2020) investigated how different navigation devices (in-sight and handheld) support human couriers during last mile delivery, and used ET to evaluate the couriers' interaction frequency with the navigation devices as well as their distraction during delivery. The results indicate that participants recognize potential hazards with higher accuracy during cycling as compared to walking. In addition, it was found that participants interacted more with the handheld devices than with in-sight displays, leading to a higher accident risk resulting from diverted attention from the interaction with the handheld navigation device.

With regard to warehousing, Renner and Pfeiffer (2017a) used two types of AR devices (monocular peripheral Google glasses and a binocular Microsoft Hololens) to compare different AR-based guidance technique (display of arrow, display of spherical waves) with non-AR pick-by-light techniques for order picking. The authors investigated whether integrating ET as a means of modulating feedback based on the user's attention improves order picking performance. They found that the use of ET leads to fewer head movements of the participants, but at the same time, the results of the NASA-TLX questionnaire show that participants report a slight increase in subjective task load when using ET. The authors also found that the binocular Hololens outperforms the monocular Google glasses and the spherical display outperforms the arrow display in terms of order picking completion time. Ulutas and Ozkan (2019) studied forklift drivers' workload considering physical, environmental, and mental factors. The authors used the Cornell Musculoskeletal Discomfort Questionnaire to assess the postural discomfort of drivers and a questionnaire combined with field measurements to assess environmental factors. ET was used to estimate mental workload. The results show that forklift drivers fixate more during travelling than during pallet loading and unloading activities, implying a higher mental workload in pallet transportation. In addition, a monotonous effect was found for all forklift tasks as the pupil size of drivers became smaller over time during all activities. The authors concluded that using ET data in combination with the questionnaires enables a comprehensive assessment of the workload of forklift drivers. Chadalavada et al. (2020) investigated how autonomous forklifts can perceive human intention and communicate forklifts' navigation intent in an industrial warehouse. The authors used ET to track human attention and found that people primarily fixate their gaze on the side of the robot they decided to pass. By receiving ET information, the robot can project its intention through spatial AR, which enables workers to actively choose safer paths during an encounter.

4.5. Summary

ET applications discussed in the manufacturing and logistics literature are summarized in Fig. 7, where the number of papers that investigate ET in both specific and macro application areas are summarized.

The main benefits of using ET in different application areas of manufacturing and logistics in terms of process performance, human performance, and work environment and safety (see Section 2.4) are summarized in Table 3 (note that "ID" refers to the paper identification code as shown in Table A2 in the Appendix).

Summarizing the methodologies used, most works contained in our sample applied ET in an experiment. While some works used only ET for collecting data, others combined ET with further methods, such as surveys, qualitative studies, simulation or data analysis. ET was often used exclusively for measuring human visual attention, as it is non-invasive and provides a more objective measurement. Mixed-method approaches were used in case researchers were interested in obtaining additional subjective data, and in this case, they were complemented by qualitative studies or surveys. These kinds of studies can be found in all application areas. Some studies also combined ET with surveys to comprehensively evaluate human workload. In these cases, ET was used to estimate mental workload, while surveys (e.g., the NASA-TLX questionnaire) were used to measure physical workload or discomfort.

Moreover, our review showed that most ET experiments were conducted in laboratory settings, and that only a few papers employed mobile ET in field settings, for example to analyse operational tasks at assembly lines, to estimate mental fatigue of forklift drivers, or to explore the navigation behaviour of couriers in last mile delivery. As argued by Wickens et al. (2004), field studies have higher practical validity compared to laboratory studies, but allow less control of experimental conditions. Technological advances in recent years have led to ET systems that are easy to use in terms of portability and quality of collected data, and more studies have employed ET in the real world to discover how the human brain and body motion interact with other systems. However, field studies are often more expensive in terms of time and cost. Indeed, we observed that several studies used college students as participants due to the difficulty of involving industrial experts. In these cases, participants might not represent the population the researchers targeted, which may reduce generalizability.

Our review also indicated interesting features about ET measures and their relationships to applications, which are summarized in Table 4. First, many studies used measures like fixation duration, number of fixations, or time to first fixation to measure how much the subject is attracted by a particular product feature. In addition, the SF ratio has been adopted to indicate the ambient or focal style of cognitive information processing by the subject, and gaze entropy has been introduced to indicate how "disordered" the subject's visual behaviour is. Position of fixations, which indicates where the eye is focused on for a specified time, was frequently used for worker's task analysis and human–machine/robot interaction in production, as a measure of estimating the worker's task intention. The variation of pupil diameter was utilized as a measure to quantify workers' mental workload. Time to first fixation and fixation duration were used to access usability of human–computer/machine interface, and the dwell time was used as a threshold to trigger the eye-based control in human–computer/machine interaction. In quality inspection, fixation duration and scanpaths were used to trace the visual strategy adopted by the inspectors for quality check and their focus during inspection.

5. Future research opportunities

5.1. Research ideas based on the literature sample

5.1.1. Joint use of ET and other technologies for workers' task analysis and assistance

The introduction of Industry 4.0-enabling technologies poses great challenges for manufacturing and logistics systems, as a transformation from technical and social perspectives is indispensable to enable the effective interaction between humans and systems (Bednar & Welch, 2020). Manufacturing and logistics systems are socio-technical systems where workers interact with the work environment. It is therefore important to understand the interaction between information processing capabilities of humans and physical equipment or tools and digital technologies (Neumann et al. 2021). As our results reveal, ET enables the unobstructive tracking of workers' visual focus during assembly and human-robot collaborative tasks. In this context, we argue that ET can be an important and useful technology that helps bring to light not only conscious, but also unconscious behaviours of workers. Indeed, some of the studies show the potentials of combining ET with other tracking technologies (e.g., spatial position tracking, hand tracking) for the prediction of workers' task intention and for differentiating between defined and applied skill levels. However, using ET and hand tracking to observe workers' activities and predict their next step intention is in its initial phase and deserves more field validation. Thus, we encourage future studies to take more task-related factors into consideration, including (but not limited to) task difficulty, demographic characteristics of workers, or working shift, to gain more insights into how ET, hand tracking, depth sensors for body tracking, and digital twins can be used jointly. This could enable a better recognition of workers' task execution in dynamic and complex manufacturing environments, and a more comprehensive evaluation of workers' performance and skills. Moreover, future studies could explore the integration of physiological tracking data with AR for intelligent worker assistance. For example, the prediction of workers' task intentions can be used as an input for AR, which allows displaying instructions to mitigate potential operational errors (Bovo et al., 2020).

5.1.2. Leverage ET to scrutinize task consistency within and between workers

Our review showed that ET was used for analysing workers' visual sequence in quality inspection. This sequence can be compared with process descriptions to understand if workers modify given processes, and if these modifications improve or worsen performance. These analyses could be transferred to other manufacturing and logistics processes, such as raw material sorting, assembly, material handling, or maintenance, to gain further insights into how workers access and eventually modify instructional information. Our results also showed that there is a performance gap between novices and experienced workers in visual inspection tasks, and that there is potential for novices to improve their performance via feedforward (a priori) display of an expert's cognitive strategy through visualization of scanpaths recorded via ET. We therefore argue that there is a need to explore the potential of integrating ET into personalized training of operational tasks, and validating the effectiveness of training by displaying feedforward information in different formats (static, dynamic, or hybrid). Moreover, future research could take learning effects into account and investigate how workers' eye movements vary over the training process, and how gaze measures can indicate learning outcomes (see Glock et al. (2019) for an overview on learning in manufacturing).

5.1.3. Integrate ET and other biometric technologies for evaluating workers' physical and mental states

Worker well-being is a key element of the Industry 5.0 vision (Dixson-Declève et al., 2022). Our review has shown that ET can be used to estimate the mental workload of workers, and that it can also be combined with wearable sensors and physiology-related technologies such as EEG, EOG or EMG to evaluate workers' physical and mental states. However, our results show that existing studies that comprehensively assess worker's mental and physical states in combination with ET are rare. We therefore encourage future studies to investigate how ET and bio-sensing technologies can be used to measure workers' well-being, and to validate the results with larger populations. Another aspect to consider is that in many countries, workforces are ageing. Understanding the mental and physical characteristics of older workers allows companies to properly support and guide them in performing their tasks (Grosse et al., 2015; Strasser, 2018). Prior research has shown that older workers may have disadvantages in completing physical and information processing tasks (Calzavara et al., 2020). Thus, we see potential for using ET and other biometric technologies to analyse the mental and physical states of older workers to understand how work processes need to be organized to meet the requirements of this worker group. Such amendments to existing work processes could help companies to overcome some challenges of the demographic change and to keep older workers on the job.

5.1.4. ET as an enabler to include people with disabilities in operational activities

One important social concern is how to involve people with disabilities in the manufacturing industry. Being employed brings the enjoyment of social contacts and enables the realization of self-esteem (Heron & Murray, 2003), in particular to people with disabilities (Eurofound, 2021; Mark et al., 2019). Our review has shown that with respect to physical interaction, eye modality can infer subject's interactive intents and trigger remote control effectively, and such benefit is particularly obvious when workers' hands are occupied. In this line of thought, we see a strong research need to explore the potential of ET in supporting handicapped workers to discover manufacturing and logistics scenarios in which people with disabilities can be involved in operational activities.

5.1.5. Get more insights from the field

Finally, we would like to highlight the experimental setting employed in the sampled works. Most papers we reviewed conducted studies in laboratory environments, and only a few were conducted in the field (see Table 1). Field studies usually provide a higher practical validity but permit less control of the experiment parameters. Given that manufacturing and logistics are complex systems influenced by various factors, we suggest that future work should put a stronger emphasis on validating findings in the field.

5.2. Research ideas transferred from ET applications in retailing

Due to the low number of works that applied ET in logistics, the future research opportunities discussed in the previous section focus mainly on the manufacturing area. Given that some activities in retailing resemble logistics processes (e.g., the travelling along the shelves of a store and the searching for items – which is a process that similarly occurs in order picking), and considering that ET has frequently been investigated in this sector, we summarize some insights for the logistics area here and discuss promising research ideas that emerge from this literature stream.

5.2.1. Transferring insights from consumer search behaviour to logistics

Pfeiffer et al. (2020), for example, used ET to examine two types of customer search behaviour: exploratory and goal-directed search. The authors predicted the customer's search behaviour using ET data and a machine learning technique and argued that ET data can be used as an input for a customer assistance system. The system could support customers by filtering out irrelevant products during goal-directed searches and by providing product recommendations in exploratory situations. As a future research opportunity, such a system could be applied in order picking warehouses, where workers usually follow goal-directed search processes to identify requested items. A support system that filters out irrelevant products could speed up the order picking process and improve quality. In addition, understanding the differences in search processes of expert and novice order pickers could help in developing training programs that better match order pickers' needs. Otterbring et al. (2019) used ET to investigate the customer search process on three levels: stock, shelf, and store. Their results show that customers tend to follow the 'easy information acquisition rule' in visualizing items in stock, i.e., they tend to move their gaze upwards along the shelf independent of the task. Moreover, when the initial shopping goal is specified, customers tend to have an equal number of fixations for different choice tasks, while when there is no specified initial shopping goal, customers fixate less during the first task and more during following tasks. The study of Otterbring et al. (2019) could be replicated in a warehousing environment to expand our understanding of how order pickers search for items on shelves, which could provide valuable information on how to provide information on shelves and how to assign items to shelf locations. Ladeira et al. (2021) used ET to examine the relationship between physical movements and the customer's visual attention. They found that movements during product selection reduce customer's visual attention. The authors also found that several factors moderate the relationship between movements and visual attention, such as the complexity of the visual context and mobile phone usage that both further reduce visual attention during movements. These results may be of relevance for order picking, where movements during item selection and the use of assistive devices may reduce the visual attention of order pickers, increasing the chance of pick errors (see Setayesh et al. (2021) for an overview of pick errors).

5.2.2. Transferring insights from the design of retail stores to warehouse design

Another stream of research that provides insights for logistics is the design of the lighting system in retail stores. Harwood et al. (2013) used ET to investigate the accent lighting effect of a merchandising unit. The authors found that the customer's attention is initially directed to accent lit areas, but that the lighting effect decreases over time such that the position of the item on the shelf becomes the dominant factor in attracting the customer's attention. Laski et al. (2020) used ET to examine how lighting with a continuous modulation of colour rendering properties impacts the customer's spatial browsing range. The authors found that the participant's attention can subconsciously be drawn towards lighting changes. More specifically, RGB lighting conditions induced participants to increase their distribution of fixations on a shelf as compared to a white lighting condition. The two studies have implications for logistics facilities, where smart lighting systems enable companies to adjust the lighting conditions to the user's needs (see Füchtenhans et al. (2021) for a recent review of smart lighting systems), as they highlight the potential of ET to evaluate the worker's visual attention under different lighting conditions. Lighting conditions might influence errors during order picking, search times, and the worker's well-being. Using ET to capture the worker's visual behaviour may help to identify lighting conditions that support the workers in their daily activities, which is a promising direction for future research.

6. Conclusion

This paper presented the results of a systematic literature review on the opportunities of using ET in manufacturing and logistics. A total sample of 71 papers was categorized and analysed according to ET applications in different manufacturing (product development, production, quality inspection) and logistics areas. Our findings give evidence of the huge potential of ET in these fields. We observed that a large share of ET research concentrated on manufacturing, where ET was used for tracking human attention, communicating between humans and machines, and detecting opportunities for improving human performance and the work environment. ET research in logistics is still scarce. To derive promising ideas for future research, we therefore discussed some works that applied ET in retailing and suggested how the insights obtained in these works could be transferred to logistics. From a methodological point of view, we found that ET has frequently been combined with other enabling technologies such as AR, VR, as well as motion and hand tracking. Experimental ET research was often complemented by other empirical research methods, such as surveys or qualitative studies. This shows that ET is a flexible technology that can be employed to answer research questions in a broad variety of different applications.

This work supports researchers by providing a systematic overview of ET applications in manufacturing and logistics. The developed framework structures the research stream and the results of the literature review synthesize the state-of-knowledge. The paper supports researchers in finding starting points for future works in this emerging research field building on the obtained insights into how workers interact with ET technology and the work environment. We argue that ET itself can give objective physiological measures to reflect human attention, and it can act as a complement to other technologies for human assistance. The bridging role that ET plays is particularly relevant in a digitalized working environment, as it helps to deeply understand the role of workers in complex and heterogeneous digitalized manufacturing settings.

Regarding managerial insights, this work supports practitioners in exploring the possibilities of using ET in assisting workers in their operational activities, e.g., to combine ET and AR for task guidance, work instructions and error signals. Managers can also employ ET (also in combination with other tools) to evaluate worker's physical and mental workload. Moreover, our results highlight opportunities of using ET to engage an ageing workforce and people with disabilities in manufacturing and logistics.

This study has limitations. First, we might have missed relevant keywords during the database search, and we may have omitted a fraction of the literature not included in the two scholarly databased we used (despite them being dominant in engineering, technology and management). However, the snowball sampling can to some extent limit any oversights. Second, a subjective bias could have occurred in the reading and selection of papers. Despite the potential shortcomings, this work makes an important contribution to its stream of research by providing a comprehensive and distinctive analysis of existing works and by highlighting research opportunities related to the application of ET for human-centred manufacturing and logistics systems, an important step towards the vision of Industry 5.0.

CRediT authorship contribution statement

Ting Zheng: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. **Christoph H. Glock:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision. **Eric H. Grosse:** Conceptualization, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Tables A1 and A2.

Table A1
Overview of frequently used ET measures.

Measure	Definition
Area of interest (AOI)	• Defines the regions in the stimulus, on which the researcher is interested in gathering data.
Position measures	
Position of a fixation	• Addresses where a participant looks, i.e., the centre of the field of vision. It is given by (x,y)-coordinates in a two-dimensional space, or (x,y,z)-coordinates in a three-dimensional space.
Nearest neighbour index (NNI)	• NNI, denoted by R, provides an indication of fixational spatial distribution, e.g., data points of fixations are ordered (R greater than 1), random ($R = 1$), clustered ($R < 1$), or maximally aggregated ($R = 0$).
Fixation duration (also known as fixation time)	• Measures the time the gaze of a participant stays in a position.
Dwell time	• Measures the sum of all fixation durations during a dwell (i.e., a visit) in an AOI, from entry to exit.
Pupil diameter (also known as pupil dilation or pupil size)	• Quantifies the diameter of the pupil. Its values are normally given in the form of pixels of the eye camera or in millimetres after calibration.
Numerosity measures	
Number of fixations (also known as fixation density)	• Quantifies how often an AOI is fixated.
Fixation rate (also known as fixation frequency)	• Measures the number of fixations per second or per minute.
Blink rate	• Measures the number of blinks per second or per minute.
Movement measures	
Saccade amplitude (also known as saccade length or saccade distance)	• Measures the distance of eye movement from one fixation to a consecutive fixation.
Saccade duration (also known as transition time)	• Measures the time the saccade takes to move between two fixations.
Saccade velocity	• Refers to the first derivation of position data with respect to time.
Gaze entropy	• Involves stationery and transition entropy. Stationery entropy measures fixation dispersion, and transition entropy depicts the extent of transition from one AOI to another.
Aggregate measures	
Attention map	• Is normally visualized using a heatmap, and describes the spatial distribution of eye movement data.
Scanpath (also known as scan pattern, search pattern, gaze sequence)	• Describes how the eye moves physically through space within a certain timespan.
Saccade amplitude fixation duration ratio (SF ratio)	• Quantifies the proportional measure of saccade amplitude to fixation duration.

Note: The above definitions were taken and revised from (Duchowski, 2017; Holmqvist et al., 2011; Jacob & Karn, 2003; Meißner & Oll, 2019).

Table A2
Overview and categorisation of the literature sample.

Manufacturing and logistics areas	ET application	ID	Citation	ET systems and experimental environment	ET measures	ET devices	Human focus perspective (referred and based on Meißner and Oll 2019)	In conjunction with other technologies	Joint use with other methods
Product development	Interpreting customer's product perception	1	Li et al. (2018)	Mobile ET in the lab	Fixation duration	Tobii pro glasses	Attention directed to stimuli	–	–
		2	Du and MacDonald (2014)	Desktop-based ET in the lab	Fixation duration, number of fixations, percentage-fixation time, first-located time	Tobii T120	Attention directed to stimuli	–	Survey
		3	Borgianni et al. (2019)	Mobile ET in the lab	Fixation duration, number of fixations, pupil diameter	Tobii pro glasses	Attention directed to stimuli	–	Survey
		4	Purucker et al. (2014)	Desktop-based ET in the lab	Time to first fixation, first fixation duration, total fixation duration	Tobii X120	Attention directed to stimuli	–	–
		5	Hyun et al. (2017)	Desktop-based ET in the lab	Fixation duration, number of fixations, looking probability of fixation location	Tobii X120	Attention directed to stimuli	–	Survey
		6	Kuo et al. (2021)	Desktop-based ET in the lab	Fixation duration	Tobii TX 300, Tobii Pro X3-120	Attention directed to stimuli	–	Survey
		7	Yang et al. (2021)	Desktop-based ET in the lab	Pupil diameter, dwell time, first saccade, number of fixations	Eyelink 1000 Plus	Attention directed to stimuli, emotional arousal	–	Survey, qualitative study, analytical model
		8	Yang et al. (2016)	Desktop-based ET in the lab	Position of fixations	Not mentioned	Attention directed to stimuli	Gesture recognition	–
		9	Li et al. (2017)	Mobile ET in the lab	Initial fixation points, distribution of fixation points, fixation duration, fixation order, pupil diameter, blink rate	Tobii pro glasses	Attention directed to stimuli	EEG	–
		10	Schmitt et al. (2014)	Desktop-based ET in the lab	Fixation time, gaze track	Not mentioned	Attention directed to stimuli, emotional arousal	EMG, GSR	Survey
		11	Wang et al. (2020)	Desktop-based ET in the lab	Blink rate, fixation time, pupil diameter, fixation count, saccade count, saccade time, blink count	Tobii pro X2-60	Attention directed to stimuli	EEG, machine learning	Data analysis
	Investigating the design process	12	Matthiesen et al. (2013)	Mobile and desktop-based ET in the lab	Scanpath, heatmap	SMI RED 250, SMI glasses	Attention patterns	–	–
		13	Nambiar et al. (2013)	Desktop-based ET in the lab	Heatmap	Tobii T60	Attention patterns	–	Survey
		14	Nelius et al. (2020)	Mobile ET in the lab	Fixation duration	SMI glasses	Attention patterns	–	Survey
		15	Maier et al. (2014)	Desktop-based ET in the lab	Pupil diameter, blink frequency,	SMI RED 4	Attention patterns	–	–

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Table A2 (*continued*)

Manufacturing and logistics areas	ET application	ID	Citation	ET systems and experimental environment	ET measures	ET devices	Human focus perspective (referred and based on Meißner and Oll 2019)	In conjunction with other technologies	Joint use with other methods
					blink duration, fixation duration				
		16	Boa and Hicks (2016)	Desktop-based ET in the lab	Saccade amplitude fixation duration ratio (SF ratio)	Tobii TX300	Attention patterns	–	–
		17	Doellken et al. (2021)	Mobile ET in the lab	Gaze entropy	Tobii pro glasses	Attention patterns	–	Survey
		18	Mehta et al. (2020)	Desktop-based ET in the lab	Fixation duration	FOVIO FX3	Attention patterns	Machine learning	Simulation, data analysis
Production	Work analysis and task guidance	19	Bhatia et al. (2015)	Mobile ET in the lab	Fixation duration	Arrington research's viewpoint	Level of processing	–	–
		20	Shotton and Kim (2021)	Mobile ET in the lab	Number of fixations, Fixation duration	Dikablis Glasses	Level of processing	–	–
		21	Amrouche et al. (2018)	Mobile ET in the field	Position of fixations, gaze distribution, nearest neighbour index (NNI)	Pupil labs	Task intent prediction	Machine learning	Data analysis
		22	Haslgrübler et al. (2019)	Mobile ET in the field	Position of fixations	Pupil labs	Task intent prediction	Hand recognition	Survey
		23	Manns et al. (2021)	Mobile ET in the field	Position of fixations	Pupil Invisible	Task intent prediction	Hand recognition, body recognition, digital twin	Simulation, data analysis
		24	Bovo et al. (2020)	Mobile ET in the lab	Position of fixations	Pupil labs	Task intent prediction	Hand tracking, machine learning	Data analysis
		25	Sausman et al. (2012)	Mobile ET in the lab	Position of fixations	Built on own	Attention guidance	–	–
		26	Ivaschenko et al. (2018)	Mobile ET in the lab	Position of fixations	Tobii pro glasses	Attention guidance	Augmented reality	–
		27	Renner and Pfeiffer (2017b)	Mobile ET in the lab	Position of fixations	Epson Moverio BT-200	Attention guidance	Augmented reality, virtual reality	Survey
		28	Renner and Pfeiffer (2017c)	Mobile ET in the lab	Position of fixations	Epson Moverio BT-200	Attention guidance	Augmented reality, virtual reality	Survey
		29	Haslgrübler et al. (2018)	Mobile ET in the lab	Position of fixations	SMI glasses	Attention patterns	–	Survey
	Evaluating mental workload	30	Nandakumar et al. (2014)	Mobile ET in the field	Pupil diameter, position of fixations	Built on own	Mental workload	–	–
		31	Straeter (2020)	Mobile ET in the field	Pupil diameter	CeyeBERMANS	Mental workload	–	–
		32	Paletta et al. (2021)	Mobile ET in the field	Position of fixations	SMI glasses	Mental workload	Perception neurons, digital twin, machine learning	Simulation, data analysis
		33	Peruzzini et al. (2017)	Mobile ET in the field	Gaze plot, heatmap	Tobii pro glasses	Mental workload	Multi-parametric wearable sensor, digital twin, motion capture system	Simulation
		34	Peruzzini et al. (2020)	Mobile ET in the field	Gaze plot, heatmap, pupil diameter	Tobii pro glasses	Mental workload	Multi-parametric wearable sensor, digital twin, motion capture system	Survey, qualitative study, simulation
		35	Van Acker et al. (2021)	Mobile ET in the lab	Position of fixations	SMI glasses	Mental workload	–	Survey

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Table A2 (*continued*)

Manufacturing and logistics areas	ET application	ID	Citation	ET systems and experimental environment	ET measures	ET devices	Human focus perspective (referred and based on Meißner and Oll 2019)	In conjunction with other technologies	Joint use with other methods
	Assessing human–computer/machine interfaces and interaction	36	Zülch and Stowasser (2003)	Mobile ET in the lab	Time to the first interaction, average fixation duration, corrected fixation rate, average saccadic length, total view path length	NAC Eye Mark Recorder; SMI glasses	Level of processing and perceptual fluency	–	Survey
		37	Wu et al. (2016)	Desktop-based ET in the lab	Time to first fixation, fixation before, gaze plot, heatmap	Tobii X300	Level of processing and perceptual fluency	–	Survey
		38	Walper et al. (2020)	Mobile ET in the lab	Fixation duration	SMI glasses	Level of processing and perceptual fluency	–	–
		39	Zhang et al. (2017)	Desktop-based ET in the lab	First-fixation time, fixation duration, pupil diameter, position of fixations, heatmap	Tobii X2-60	Level of processing and perceptual fluency	–	–
		40	Lušić et al. (2016)	Mobile ET in the lab	Fixation duration, fixation rate	Tobii pro glasses	Level of processing	–	–
		41	Heinz et al. (2020)	Mobile ET in the lab	Position of fixations, scanpath	Tobii pro glasses	Visual patterns	–	Survey
		42	Tang et al. (2019)	Mobile ET in the lab	Fixation duration, dwell time, heatmap	SensoMotoric's BeGaze	Situational awareness	–	Survey, qualitative study
		43	Bardins et al. (2008)	Mobile ET in the lab	Position of fixations, dwell time	EyeSeeCam	Visual control	Head tracking	Survey
		44	Jungwirth et al. (2018)	Mobile ET in the lab	Dwell time	Pupil Labs	Visual control	–	Survey
		45	Guo et al. (2013)	Webcam ET in the lab	Position of fixations	Panasonic HDC-SD60	Visual control	–	Survey, analytical model
		46	Zhao et al. (2021)	Desktop-based ET in the lab	Position of fixations	Tobii 4c	Task intent prediction	Hand recognition	Simulation
		47	Li et al., (2021)	Desktop-based ET in the lab	Position of fixations	Tobii nano	Task intent prediction	Spatial camera	–
	Facilitating human–machine/robot collaboration	48	Palinko et al. (2016)	Webcam ET in the lab	Position of fixations	iCub's eye	Task intent prediction	Head tracking	Survey
		49	Admoni and Srinivasa (2016)	Mobile ET in the lab	Position of fixations	Pupil Labs	Task intent prediction	–	Analytical model
		50	Fan et al. (2020)	Mobile ET in the lab	Position of fixations	Tobii pro glasses	Task intent prediction	Motion capture system	Analytical model
		51	Berg et al. (2019)	Desktop-based ET in the lab	Position of fixations, blink rate	Gazepoint	Task intent prediction	Gesture recognition	–
		52	Paletta et al. (2017)	Mobile ET in the lab	Volumes of interest (VOI)	SMI glasses	Situational awareness	Motion capture system	Survey
		53	Dini et al. (2017)	Mobile ET in the lab	Look rate, average dwell time, turn rate, nearest neighbour index (NNI)	SMI glasses	Situational awareness	Motion capture system, machine learning	Survey, data analysis
		54	Paletta et al. (2019)	Mobile ET in the lab	Volumes of interest (VOI)	SMI glasses	Situational awareness	Motion capture system	Survey
		55				Tobii pro glasses		–	

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Table A2 (*continued*)

Manufacturing and logistics areas	ET application	ID	Citation	ET systems and experimental environment	ET measures	ET devices	Human focus perspective (referred and based on Meißner and Oll 2019)	In conjunction with other technologies	Joint use with other methods
Quality inspection	Investigating quality inspection patterns		Schlösser et al. (2016)	Mobile ET in the field	Gaze plot, heatmap, cluster		Attention patterns		Survey, qualitative study
		56	Niemann et al. (2019)	Mobile ET in the field	Gaze plot, heatmap, cluster	Tobii pro glasses	Attention patterns	–	Survey
		57	Tuncer et al. (2020)	Mobile ET in the field	Total fixation duration, number of fixations	Tobii pro glasses	Attention distribution	–	–
		58	Ozkan and Ulutas (2016)	Mobile ET in the field	Total visit duration, average visit duration, visit count, total fixation duration, average fixation duration, number of fixations, average number of fixations, pupil diameter, heatmap	Tobii pro glasses	Attention patterns and level of processing	–	–
		59	Ulutas et al. (2020)	Mobile ET in the field	Number of fixations, total fixation duration, visit count, average visit duration, time to first fixation data, heatmap	Tobii pro glasses	Attention patterns	–	Simulation
		60	Aust et al. (2021)	Desktop-based ET in the lab	Gaze plot, heatmap	Tobii pro spectrum	Attention patterns	–	Survey
		61	Huang et al. (2020)	Desktop-based ET in the lab	Gaze proportion for inspection, gaze proportion for response entry	SMI REDn	Cognitive hacking	EEG	–
	Quality inspection training	62	Wang et al. (1997)	Desktop-based ET in the lab	Fixation sequence	ASL 210	Attention patterns	–	–
		63	Duchowski et al. (2000)	Virtual reality simulation in the lab	Position of fixations	ISCAN eye tracker	Attention patterns	Virtual reality	–
		64	Sadasivan et al. (2005)	Virtual reality simulation in the lab	AOI, sequence of fixations, time spent at each area of interest, total number of fixations, total number of fixation groups, mean fixation duration	ISCAN eye tracker	Attention patterns	Virtual reality	Survey
		65	Bowling (2010)	Virtual reality simulation in the lab	Sequence of fixations, number of fixation points, number of fixation groups, mean fixation duration, percent of area covered	ISCAN eye tracker	Attention patterns	Virtual reality	–
		66	Nalanagula et al. (2006)	Desktop-based ET in the lab	Scanpath	ISCAN eye tracker	Attention patterns	–	Survey
		67	Nickles et al. (2003)	Desktop-based ET in the lab	Number of fixations, fixation time,	ASL Stationary Optics ET System	Attention directed to stimuli and	–	–

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Table A2 (*continued*)

Manufacturing and logistics areas	ET application	ID	Citation	ET systems and experimental environment	ET measures	ET devices	Human focus perspective (referred and based on Meißner and Oll 2019)	In conjunction with other technologies	Joint use with other methods
					saccade distance, number of eye movements in the horizontal direction		level of processing		
Logistics	ET applications in logistics	68	van Lopik et al. (2020)	Mobile ET in the field	Number of fixations, fixation duration	Tobii pro glasses	Situational awareness	–	Survey
		69	Renner and Pfeiffer (2017a)	Virtual reality simulation in the lab	Position of fixations	Pupil Labs	Attention guidance	Augmented reality, virtual reality	Survey
		70	Ulutas and Ozkan (2019)	Mobile ET in the field	Number of fixations, fixation duration, pupil diameter variation	Tobii pro glasses	Mental workload	–	Survey
		71	Chadalavada et al. (2020)	Mobile ET in the lab	Number of fixations, percentage of fixations on AOI	Pupil Labs	Task intent prediction	Spatial augmented reality, motion tracking	Qualitative study

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