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Value by Design: Reducing Cognitive Load by Using Visual Guidance in Augmented Reality - An Eye-Tracking Study

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Value by Design: Reducing Cognitive Load by Using Visual Guidance in Augmented Reality- An Eye-Tracking Study

Completed Research Paper

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Abstract

Besides the positive effects of Augmented Reality (AR) on work and learning performance, research on its impact on cognitive load has generated ambiguous results. Therefore, this study investigates the effects of visual guidance in AR on cognitive load by highlighting essential virtual input depending on their necessity to the work and learning task. We developed an AR application and ran a training session in a learning factory by experimentally (N=55) investigating two AR applications, with or without visual guidance, compared to paper instructions using questionnaires and eye-tracking. Our data reveal that participants using AR with visual guidance perceived less cognitive load than those without visual guidance or paper instructions. Eye-tracking provides insights into cognitive load changes over three learning rounds, showing that visual guidance is beneficial, especially at the beginning of learning. Based on our findings, we recommend integrating visual guidance into AR work and learning applications, especially for novices.

Keywords: Augmented Reality, Cognitive Load, Eye-Tracking, Visual Guidance, Learning and Training, Design Guidelines

Introduction

Especially in work environments where hands-on knowledge is needed, Augmented Reality (AR) adds value by assisting in the work process (Bräker et al., 2023; Buchner et al., 2022), e.g. maritime navigation (Bräker & Semmann, 2022), technical customer service processes (Niemöller et al., 2019), care work (Prilla et al., 2019), assembly and maintenance (Bläsing & Bornewasser, 2021), or emergency management decisions (Mirbabaie & Fromm, 2019). Beyond increased productivity and reduced error rates, AR also benefits learning and training (Mohammadhossein et al., 2024; Sommerauer & Müller, 2018) by providing visualized instructions, parameters, or safety warnings (Daling & Schlittmeier, 2022; Hou et al., 2013). Due to the industrial environment's transformative nature, lifelong learning is critical for organizations to maintain competitiveness and innovative strength (Sautter & Daling, 2021). Using AR for workplace-integrated learning and training allows workers to learn in a genuine work setting while maintaining feedback on task execution and the realism of newly acquired skills.

Despite AR's potential benefits, its practical application still needs to be improved due to significant barriers for monetary and resource-oriented reasons why, e.g., researchers provide recommendations for designing AR authoring tools to facilitate AR creation and development (Bräker et al., 2023). However, one critical obstacle in determining long-term use and learning is the human perception of the technology's usability (Berkemeier et al., 2018; Davis, 1989; van der Heijden, 2004). Schein & Rauschnabel (2021) report employees' reservations, such as concerns of being overwhelmed or distracted by too much information or unfamiliar interaction techniques, preventing long-term technology acceptance and usage (Bläsing & Bornewasser, 2021). A pivotal challenge to usability is the additional cognitive load imposed on users when engaging with AR (Buettner et al., 2018; Drouot et al., 2022; Schein & Rauschnabel, 2021). The cognitive load describes the demand on the human's working memory arising from, e.g., a learning or work task since the working memory's capacity to store and process information is limited (Duran et al., 2022; Sweller et al., 2019). An unintended cognitive load can arise from integrating virtual (3D-) elements, instructions, or additional AR screens, which can overload the worker instead of providing added value. While research confirms the link between cognitive overload and declining learning and working performance (Souchet et al., 2022), research on AR usage shows conflicting results regarding whether using AR reduces or increases cognitive load (Buchner et al., 2022; Drouot et al., 2022; Mirbabaie & Fromm, 2019).

The unstructured display of AR information can demand the worker since the brain must simultaneously process various physical and virtual stimuli. Therefore, AR must follow a meaningful design considering strategies addressing the cognitive load (Buchner et al., 2022). This challenge is especially notable when employing AR in learning contexts, as novices typically require more time to process new information. During information processing, information gets into the working memory, undergoes processing, and subsequently gets structured within pre-existing cognitive schemas in the long-term memory. Individuals engaged in learning possess limited or loosely connected cognitive schemata to organize incoming information efficiently (Baddeley, 2021; Brünken et al., 2019; Kalyuga, 2023; Mayer, 2024), which is why research confirms differences in information processing between experts and novices (Sweller et al., 1998). Since the working memory that processes information can only handle a limited amount of information, excessive task demands, or information load can overwhelm the working memory's capacity. However, AR unspecific multimedia principles like the Cognitive Load Theory of Multimedia Learning (CTML) suggest guidelines for designing learning environments considering cognitive architecture (Mayer, 2021). For example, recommendations are to structure the amount of information presented, provide visual orientation, or provide temporal and spatial integrated information (Lin & Tsai, 2021; Mayer, 2021). Otherwise, an insufficient information presentation can lead to less learning due to overload, frustration, and failure (Mayer, 2024; Sweller et al., 2019).

However, despite these efforts, a systematic literature review shows that no study has investigated the possibility of the AR guidelines' transferability (Çeken & Taşkın, 2022). In response to the research gap and challenge of designing AR that cognitively supports work and learning rather than overwhelms, this paper investigates how visual cues can guide through information processing of new information. Signaling describes visual guidance that intends to reduce the cognitive load imposed on the learner by directing attention, as Rodemer and colleagues (2023) investigated for digital learning. Utilizing visual cues assists in concentrating on relevant elements of a presentation, which becomes essential when additional information from several sources, like virtual and physical information in the context of AR, is presented to a novice. Therefore, we integrate virtual guidance into the AR application and investigate the usefulness of guiding attention to essential elements.

With our first research question (RQ), we examine whether adding visual guidance in the form of, e.g., arrows and frames offers value for designing AR. The hypothesis is that providing orientation and guidance should contribute to moderating the cognitive load, addressing the following RQ:

RQ1: *Does integrating visual guidance in AR applications mitigate the perceived cognitive load in a work and learning task?*

Based on literature in comparable learning contexts, we hypothesize the following:

H1: U*sing visual guidance in AR applications mitigates the perceived cognitive load in a work and learning task.*

Secondly, AR applications have been "one-size-fits-all" solutions providing the same explanations regardless of individual information processing. However, adapting the presented information to align with individual learning processes and preferences could mitigate the cognitive load and foster learning outcomes. So far, the evaluation of AR applications on their cognitive impact mostly uses interviews or questionnaires, which reflect the respondents' impressions at one point in time after the entire usage. However, a real-time impression of the course of use must be obtained to investigate and provide individualized learning. Using physiological data, as aimed for research in NeuroIS (Morana et al., 2017; Shojaeizadeh et al., 2019) or Human-Computer-Interaction (Bläsing & Bornewasser, 2021; Kosch et al., 2018; Zagermann et al., 2018), provides real-time insights into cognitive load responses and completes the informative value of questionnaires. Based on previous research (Buettner et al., 2018; Vasseur et al., 2023), this study states the need for an additional methodology that enables continuous user tracking over AR usage. Static eye-tracking in desktop applications found its way into IS research practice, e.g., for evaluating web design (Djamasbi et al., 2008), decision-making and user performance (Buettner et al., 2018; Shojaeizadeh et al., 2019), digital learning (Liu et al., 2022; Rodemer et al., 2023), or marketing (Kim & Lee, 2021). However, as a literature review by Vasseur and colleagues (2023) indicates, mobile eye trackers still need to be used. The added value of the present study lies in integrating eye-tracking into the use of AR head-mounted displays (HMD). It provides gaze data, allowing conclusions on cognitive load during work and learning. Therefore, this paper aims to provide real-time insights to enable holistic investigations of cognitive load throughout AR usage by addressing RQ 2:

RQ2: *Does the integration of visual guidance in an AR application affect cognitive load continuously measured with eye-tracking throughout usage?*

To address the RQs, we developed an AR application that we used in a manufacturing setting. We conducted an experimental study with 55 participants using the AR application with or without visual guidance. We tested both AR applications against paper instructions, which we used as a baseline condition. The experiment combined a subjective evaluation of the effects on cognitive load (RQ 1) with an objective eye-tracking-based investigation (RQ 2).

Firstly, our findings contribute to ambiguous AR usage and cognitive load research by providing real-time data throughout and after usage. Secondly, since our study shows that only the AR application with visual guidance benefits paper instructions, we stress the need for meaningful AR design, especially during initial learning. Thirdly, our findings investigate the potential for more individualized learning based on insights gained from eye-tracking data. Our research highlights the importance of considering and exploring human factors such as information processing support and cognitive load in design technologies.

The paper is structured as follows: It provides the technological basics of AR, cognitive load, and eye-tracking measurement. In the third section, we present the development of the AR application based on previous literature. In the fourth section, we report the experimental approach and show the results in the fifth part. In section six, we discuss the findings and implications and close with section seven with the conclusion.

Related Work

The concept of AR describes the overlay of virtual, computer-generated perceptual data onto the physical environment, offering learners additional information and guidance (Daling & Schlittmeier, 2022; Hou et al., 2013). The distinct characteristics of AR depend on the type of display utilized, which may include HMD and glasses, handheld displays like smartphones and tablets, and spatial displays (Buchner et al., 2022). With AR, information can be integrated into work processes, providing contextual insights and real-time assistance for applying learning materials by overlaying or connecting the real-world setting with virtual objects (Azuma, 1997; Speicher et al., 2019). Research on AR has surged as it emerged as a promising solution for delivering supplementary information and crucial cues essential for process-integrated learning. Systematic reviews and meta-analyses compiled the chances of AR-enhanced learning specifically for industrial settings (Howard & Davis, 2023; Wang et al., 2022).

Cognitive Load and Visual Guidance

However, in addition to the advantages of AR, which lie in the cognitive support of people, inconsistencies in research show that AR can also lead to cognitively overloading people. Various terms are used to characterize the cognitive demand experienced by humans, such as "cognitive workload", "cognitive load", or "mental workload" (Ayres et al., 2021; Kosch et al., 2023). The similarity between the terms exists in the idea that the human cognitive load refers to the amount of information a person can process during a specific time, which is restricted due to the limited capacity of the human working memory (Parong & Mayer, 2021; Sweller et al., 2019). The term cognitive load (Sweller et al., 1998), which is frequently used in the learning context, distinguishes between three sub-dimensions: intrinsic load (ICL) refers to the learning material's complexity and learner-based skills to recognize schema and structures (e.g., prior knowledge), extraneous load (ECL) influenced by external stimuli like the learning environment's instructional and didactical design and germane load (GCL) that refers to linking new content from working memory with each other and with existing knowledge (Kalyuga, 2023; Sweller et al., 2019). Other concepts distinguish between two sources from which cognitive load can arise: learner-based dimension (mental effort) and task-based dimension (mental demand) (Paas et al., 1994). This paper uses the term and concept of cognitive load since it relates to learning tasks, and it uses ECL to specify the load that results from the instructional design of the learning content. A consensus exists that excessive cognitive load impedes learning and work performance, so technology design should strive to mitigate unnecessary cognitive load (Mayer, 2024; Morrison et al., 2014).

Mayer (2014, 2021) developed the CTML based on the limited working memory capacity and cognitive load theory. The theory provides evidence-based principles for designing multimedia environments, and its effects have been successfully replicated over the past years (Mayer, 2024; Sweller et al., 2019). Existing design principles recommend structuring the content or using visual cues and highlights to emphasize pertinent segments of learning materials (Mayer, 2024). One example is the signaling principle that recommends using, e.g., highlights and signposts to aid learners in distractions posed by irrelevant details. Albus & Seufert (2022) report the benefits of learning performance and cognitive load in the VR learning context. Rodemer and colleagues (2023) used visual cues for video-based learning. The authors found significant differences between pupil diameter in the signaling/no signaling condition and correlations between the self-reported cognitive load rating and pupil diameter.

The CTML principles originate from multimedia learning, which describes every learning based on text and picture, and research has confirmed using design principles mostly in non-AR contexts (Niegemann & Heidig, 2012). A systematic literature review by Çeken and Taşkın (2022) highlights that, to that date, no paper has investigated the effectiveness of multimedia principles in AR. Nevertheless, using AR extends the combination of text and pictures, combining physical and virtual information from different visual (text and picture), audio (sounds and spoken information), and physical interactions. Due to the expansion of design options beyond text and picture, given by the AR specifics, it is necessary to determine to what extent existing guidelines can be transferred to AR (Buchner et al., 2021; Çeken & Taşkın, 2022).

Measuring Cognitive Load

Methods to assess the cognitive load can be distinguished into subjective methods, meaning self-reports and questionnaires, and objective methods, like performance data and physiological methods. Cognitive load questionnaires mainly enable a retrospective assessment after a work task or learning. Examples are those from Klepsch and colleagues (2017) and Leppink and colleagues (2013), who assess the cognitive load on the ECL, ICL, and GCL subdimensions. Another frequently used method is the NASA-TLX (Hart, 1986), initially designed to measure a pilot's workload during flight. Questionnaires are characterized by their time-saving applications and easy analysis (Kosch et al., 2023). However, adaptations must be based on input multiple times throughout the learning to envision more individualized learning. Continuous assessment methods like eye-tracking are more suitable since repeated use of questionnaires causes problems. Not all questionnaires are suitable for repeated measurements, and memory effects can influence the results. In addition, filling out a questionnaire always takes the learner out of the learning experience (Suzuki et al., 2023; Zagermann et al., 2016).

Alternatively, physiological methods can be used to continuously assess cognitive load over the learning. Unlike other physiological data, such as Electroencephalography (EEG), heart rate, and electrodermal activity, eye-tracking is an easy-to-apply, non-invasive measurement that does not need additional accessories (Buettner et al., 2018) since it can be integrated into AR HMDs. Both stationary and mobile eye trackers offer a means to evaluate the metrics. Stationary eye trackers are typically installed above or below a computer screen, requiring individuals to maintain still and sometimes position their heads in a fixed holder on the table. On the other hand, mobile eye-trackers are fixed to a person's head. They can take the form of glasses or HMDs, such as those used in AR, as demonstrated by Suzuki and colleagues (2023) and (van der Meulen and colleagues (2017), or virtual reality (VR), as discussed by Souchet and colleagues (2022).

Eye-tracking enables the mapping of cortical activity, eliciting subtle nervous reactions in eye movements and slight pupil dilation, which facilitates the mapping of cognitive load as cortical activity. Eye-tracking metrics can be distinguished into saccades and fixations. Fixations denote instances where the eye maintains a relatively stable position for a duration typically between 200 and 300 milliseconds, while saccades represent the swift movements that transpire between fixations. Notably, saccades exhibit a considerable briefer duration, lasting approximately 40 milliseconds (Zagermann et al., 2016). Fixation of specific targets indicates deeper processing of information. Several metrics can be derived from that, e.g., fixation count, dwell time, and saccade duration (for a systematic review of eye-tracking metrics, see Mahanama et al., 2022; Suzuki et al., 2023; Vasseur et al., 2023). An area of interest (AOI) marks areas relevant to the application context, and fixation can be related to a specific AOI. They can be used to assign meaning to eye-tracking metrics and enable context- and content-specific analysis.

Eye-tracking allows conclusions on the cognitive load a person experiences during a work task or learning. Studies indicate that as task difficulty and cognitive load intensify, the duration of fixations and the frequency of saccades tend to increase (Bläsing & Bornewasser, 2021; Chen et al., 2011; Zagermann et al., 2018). Furthermore, the surge in saccade frequency could suggest unclear instructions, while a higher number of fixations on learning materials may indicate concerted efforts to comprehend and retain the information thoroughly. In addition to fixations and saccades, other metrics can be used since pupil diameter, blink rate variations, and scan paths are valuable indicators of an individual's cognitive state (Kosch et al., 2018). Buettner and colleagues (2018) investigated pupil diameter in three complex tasks. They found that pupil variability predicts user performance.

Methodology

This chapter explains the study design, tasks, and apparatus. The experiment was conducted to answer the postulated research questions and test the effects of virtual guidance in AR on cognitive load and changes in eye-tracking metrics during a work and learning task. The impact of AR with visual guidance and AR without visual guidance is tested compared to paper instructions. The research data is compared between three groups on the between-subject level and between the three learning rounds on the within-subject level. The study design complied with the approval of the ethics committee of the authors' research institute.

Sample

Sixty-eight people participated in the study. 13 data sets had to be excluded from the data analysis because of technical errors during the calibration of the AR HMD or on the production line. Therefore, data from 55 participants (23 female and 32 male), ages 18 to 36 (m = 24.2, sd = 3.6), were integrated into the data analysis. The participants were recruited via mailing lists and announcements at several universities and randomly assigned to one group, either AR with visual guidance (N= 24; 44.5%), AR without visual guidance (N= 18; 33.3%) or paper instructions (N= 12; 22.2%). Before the experiment, people were asked about their experience with AR. 58.1% said they had never used AR before, 38.2% said they had rarely used AR, and 3.6% said they had used AR occasionally. We also tested previous experience in an industrial/production setting, with 82% stating no experience.

Setting

The experiment is implemented in a learning factory at the University of Potsdam, Germany, a hybrid simulation environment with several working stations, robots, and simulated warehouses. A production line system transports workpieces between workstations and warehouses. The participants slipped into the role of a worker working at the production line producing optical lenses. The workstation comprises a machine terminal and an assistance system (tablet fixed in the work area). The participants were informed that in the next 20 minutes, they would be trained to manufacture a new product, optical lenses. The participants carried out different work steps. The process involved checking the order, configuring the machine parameters, monitoring the process, and performing quality control (Table 1). The participants performed three learning rounds. The instructions were presented using an AR HMD in the AR condition. The exact instructions were presented in the baseline condition via paper.

Step	**Subtask**
Step 1:	Checking order number: Compare the order number of the workpiece with the order list (assistance system). Register work operation when the order number is correct.
Step 1 *opt*	Correct the order number if necessary. Register work operation.
Step 2:	Starting calibration for checking workpiece parameters.
Step 3:	Confirm calibration.
Step 4:	Check machine parameters using the order list.
Step 4 *opt*	Correct machine parameters if necessary.
Step 5:	Start manufacturing. Meanwhile, observe the machine's condition (temperature and pressure).
Step 6:	Report back operation. Check product quality by giving the number of correct and incorrect products.

Table 1. Overview of the Production Process, Giving Subtasks per Process Step

AR Application

The developed AR application was created with Unity 2020 *(https://unity.com/de)* for the Microsoft HoloLens 2 *(https://www.microsoft.com/en-us/hololens)*. Using an HMD, the participants could perform hands-free on the machine while instructed. The participants had no prior knowledge of machine operating, so the process was taught in parallel using detailed step-by-step instructions. The application visualizes an instruction window in the field of view above the machine terminal (see Figure 1). Using text and pictograms, the application guides the participants through the process and provides audio-visual feedback about the correctness of the task (confirming sound). The level of visual guidance varied between the two AR conditions. For participants using AR with visual guidance, necessary information on the machine or assistance system was emphasized with frames and arrows pointing at the relevant areas. For example, if the order number of the workpiece needs to be compared with the number on the assistance system (Step 1), the AR application highlights both areas and guides the view with blue arrows, as shown in Figure 1. Participants using AR without visual guidance received no additional information beyond the step-by-step instructions. The AR instruction was controlled using a combination of automated navigation and voice control. For this purpose, the AR instruction was synchronized with the production line via an MQTT interface, a standard messaging protocol for the Internet of Things (IoT). This allows the application to react to the progress of the production process. In addition, voice commands (next/back) could be used to navigate the instructions. Further interaction options with the AR application were unnecessary for the use case, so they were omitted. The traditional paper instruction, used as a control condition, received the exact text and images as the AR instruction window. It was fixed on a clipboard next to the machine.

Figure 1. An Example of Using AR with Visual Guidance with Frames and Arrows Highlighting Necessary Information in Addition to the Instruction Screen

Measurements

Questionnaire responses (RQ1) were integrated with eye-tracking measurements (RQ2) to address the research inquiries.

Eye-tracking: Throughout the process, eye-tracking metrics were conducted within the AR application (HoloLens, following Kapp et al., 2021). The HoloLens 2 provides eye-tracking with a sampling rate of 30 Hz. Participants assigned to the paper-based condition wore the AR glasses solely for eye-tracking purposes, with AR overlays and interactions deactivated. This approach allows for consistent eye-tracking measurement while mitigating potential confounding variables such as the physical weight of the glasses and any associated visual impairments. Eye-tracking was implemented through the AR-Eye-Tracking-Toolkit (ARETT, *https://github.com/AR-Eye-Tracking-Toolkit/ARETT),* which provides cartesian coordinates of the eye movement and the possibility of predefined AOI. By assigning these AOIs to the relevant areas of the production process (instruction, machine terminal, workpiece, and assistance system), the eye movements could be related to the corresponding areas.

Cognitive Load: After completing all three learning rounds, the participants answered the cognitive load scale developed by Klepsch and colleagues (2017). The scale consists of eight items answered on a 7-point Likert scale from 1 (*absolutely wrong*) to 7 (*absolutely right*). Example items are: *"During this task, it was exhausting to find the important information", "The design of this task was very inconvenient for learning",* or *"During this task, it was difficult to recognize and link the crucial information"*.

Task Completion Time. The task completion time was measured between the arrival of the workpiece and completing the last subtask. It was calculated for each learning round. Only identical steps across all three learning rounds were included in evaluating the results. Steps 1 opt and 4 opt (Table 1) were varied in learning rounds two and three to keep the subjects' attention (attention check). Therefore, the participants had to correct the workpiece number (1 opt) or the machine parameter (4 opt). The optional steps were evenly distributed across the groups and participants to prevent potential distortion. Since these instruction steps have not occurred in learning round 1, both steps were excluded from the calculation to ensure comparability of the eye-tracking metrics and task completion time across all three learning rounds.

Procedure

The data acquisition occurred at the University of Potsdam, Germany, between November 2023 and January 2024. Before starting the experiment, the participants agreed to voluntary participation and the option to drop out at any time. Then, the participants were told the study's overall intent. They were briefly introduced to the learning factory, the production setting, and how to work on their workstations. After giving informed consent, participants answered the first questionnaire assessing demographic variables (age, gender, employment), experience with AR, and experience working in a production setting. Then, the participants were randomly assigned to their learning medium, followed by the calibration process of the

HoloLens for all the participants. The AR group received a short introduction to interacting with the AR HMD. Afterward, the participants started the experiment. The production process started after a workpiece arrived. The participants had to complete a six-work-step production round. The participants performed three production rounds with instructions, which are learning rounds. Table 1 shows the subtasks one to six required in each learning round. All participants received the exact same text as learning instruction. The control group received paper instructions, and the two treatment groups received information via AR with the HMD. The paper instructions were on three pages, chronologically following the production process steps. Eye-tracking data was collected during the three learning rounds. After completing all three production rounds, participants removed the AR HMD and answered the final questionnaire on a tablet. Figure 2 provides an overview of the procedure.

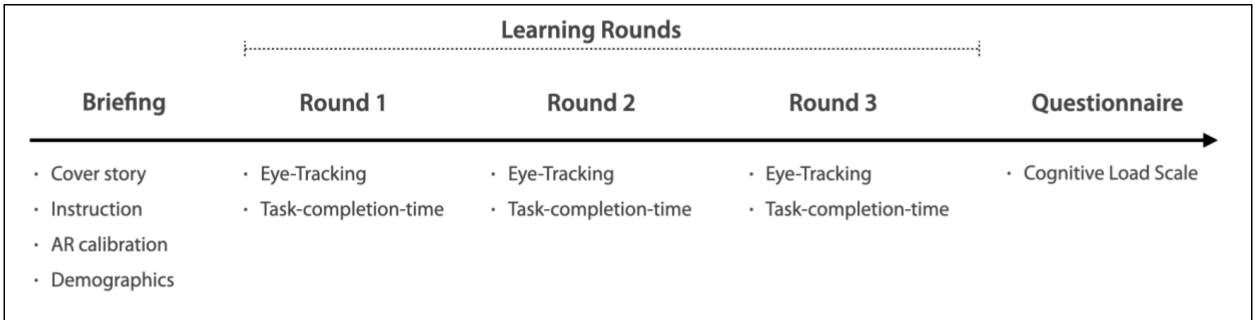


Figure 2. Illustration of the Experiment Procedure

Data Analysis

RStudio (Version 2022.12.0+353) was used for statistical analysis. The eye-tracking data was processed using the functions provided by the ARETT R package *(https://github.com/AR-Eye-Tracking-Toolkit/ARETT-R-Package.git*, Kapp et al., 2021). The gaze data was divided into fixations and saccades using the AOI classifier. The function classified every gaze on an AOI with a dwell time of over 100 milliseconds as a fixation, and all other gaze points as saccades. As a result, four eye-tracking metrics can be derived: the number and duration of fixations and the number and duration of saccades. As the eye-tracking metrics were collected during the production process, they can be assigned to the respective rounds (1-3) and steps. Overlapping fixations and saccades, which begin in one step and end in the next, were ignored for the data analysis to avoid distortion. Calculations based on an average saccade or fixings resulted in an exclusion percentage of 3.7% for ignored fixations and 1.5% for ignored saccades.

The research data (fixations, saccades, cognitive load questionnaire, task completion time) is compared on a between-subject level between three groups and for fixations and saccades also on a within-subject level between the three learning rounds. The cognitive load questionnaire data and the task completion time were analyzed using ANOVA calculations. We used the Levene test to verify sphericity across all measures as a prerequisite for ANOVA. *False Discovery Rate* corrections (fdr) were applied to all post hoc tests (corrected alpha value of .05) to mitigate the risk of Type I errors.

Results

This section outlines the examination of the gathered data. To ensure that there were no systematic differences between the groups that potentially affected the outcomes, we tested the distribution of the sample characteristics (age, sex, prior experience with AR, and prior experience with production) between the three groups. The calculation revealed no significant differences (*p-value*, Kruskall-Wallis: Experience with AR p = .78; Experience with Production p = .58; Age p =.62; Sex p = .71).

The entire production lasted, on average, 7 minutes and 35 seconds. The production time includes all times when learning information was presented or the participants were required to perform tasks. The calculation excluded the intervals in which the production line continued without learning activities.

Cognitive Load

We used the ECL subscale of the cognitive load scale developed by Klepsch and colleagues (2017) to detect differences in cognitive load that arise from the specific instructional design. Participants rate the cognitive load on three items on a scale between 1 (*absolutely wrong*) and 7 (*absolutely right*), which results in a cognitive load rating between 3 and 21 points. Figure 3 depicts the differences in cognitive load.

Since the Levene test showed no unequal variances in the conditions (p = .24), we continued with the ANOVA calculation. The ANOVA revealed a significant difference between the groups ($F_{1,51} = 5.021$, $p < .05$). Subsequently, a post hoc test depicted that the assessment of the cognitive load of participants in the AR condition with visual guidance differed significantly from those in the AR condition without visual guidance ($p < .01$) and the paper-based condition ($p < .01$). Participants learning with AR with visual guidance perceived less cognitive load (m = 6.7, sd = 2.68) compared to participants using AR without visual guidance (m = 8.3, sd = 4.16) or paper instructions (m = 8.3, sd = 3.62). The assessment of cognitive load in the AR condition without visual guidance and the paper-based condition showed no significant difference ($p > .05$).

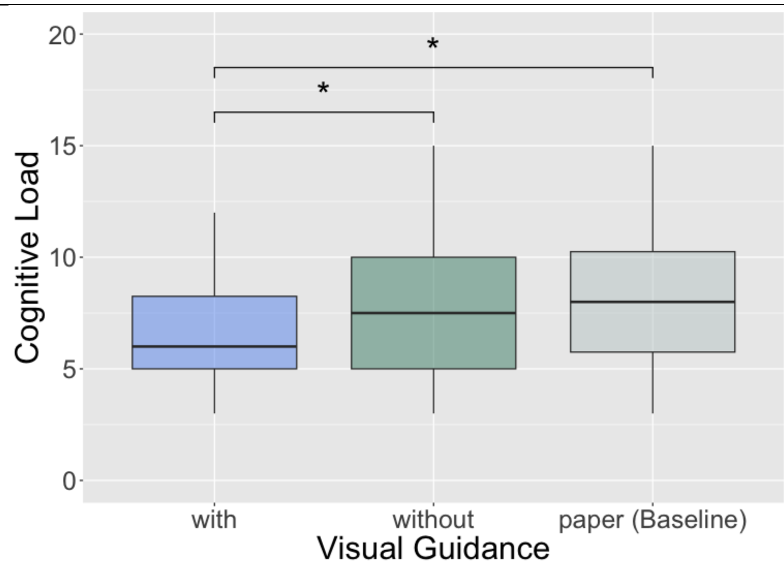


Figure 3. Perceived Cognitive Load per Instruction: AR with Visual Guidance (blue), AR without Visual Guidance (green), and Paper Instruction (grey)

Eye-tracking

We calculated four eye-tracking metrics: fixation duration, number of fixations, saccade duration, and number of saccades, specifically to the AOI described. Looking into the eye-tracking metrics over all three learning rounds, participants using AR with visual guidance showed the lowest values in all four metrics. The most considerable difference is shown for fixation duration and number of saccades. Participants using AR with visual guidance show fewer saccades and shorter and fewer fixations than paper instructions. Table 2 summarizes the findings.

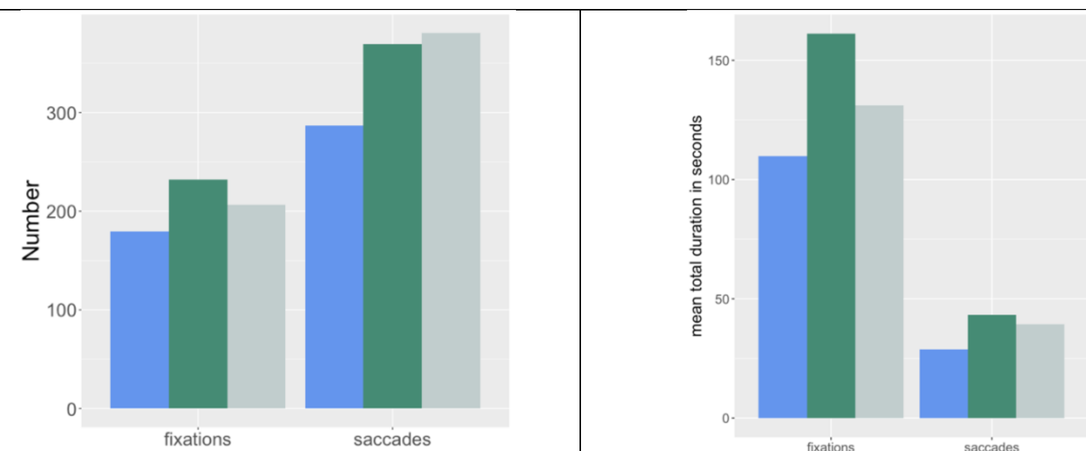
Comparing the eye-tracking metrics over time reveals differences between learning rounds 1-3 and the three conditions. Figure 5 summarizes the changes in eye-tracking metrics throughout the three learning rounds and depicts that saccades and fixations decrease throughout learning in all three conditions.

In learning round 1, participants using AR without visual guidance started with a more extended fixation, followed by paper instructions and AR with visual guidance. Participants using AR without visual guidance or paper instructions showed more saccades with a longer duration in learning round 1. The difference between the conditions was most considerable in learning round 1. Figure 4 depicts the eye-tracking metrics for the first learning experience (learning round 1). Then, the differences between the conditions converged over the learning.

Eye-tracking Metric	**AR Instructions**		**Paper Instruction**
	with visual guidance	without visual guidance	
Saccade Duration	28.7 (sd = 25.3)	43.2 (sd = 41.8)	39.4 (sd = 24.6)
Fixation Duration	109.8 (sd = 36.2)	161.1 (sd = 135.9)	131 (sd = 55.8)
Saccade Count	286.7 (sd = 122.3)	369.6 (sd=236.6)	380.8 (sd = 190.4)
Fixation Count	179.2 (sd = 64.7)	231.7 (sd= 168)	206.2 (sd = 83)

Table 2. Summary of Eye-tracking Metrics per Instruction Presented as Mean Value with Standard Deviation (sd)

The calculation of an ANOVA with repeated measurements showed significant main effect of learning rounds for fixation duration ($F_{1.7\ 85.3} = 35.4$, $p < .01$), saccade duration ($F_{1.7\ 87.1} = 3.5$, $p < .05$), number of fixations ($F_{1.8,\ 91.5} = 38.3$, $p < .01$) and number of saccades ($F_{1,\ 102} = 44.8$, $p < .01$) which shows that summarized overall conditions the characteristics of each metric change over time. However, learning with AR with or without visual guidance or paper instructions yielded no significant main effects ($p > .05$), and neither did the interaction between both ($p > .05$). Figure 5 summarizes the changes in eye-tracking metrics throughout the three learning rounds.



(1) (2)

Figure 4. Eye-tracking Metrics: Number of Fixations and Saccades (1), and Fixation Duration and Saccades Duration (2) for Learning Round 1. Metrics for AR with Visual Guidance (blue), AR without Visual Guidance (green), and Paper Instruction (grey)

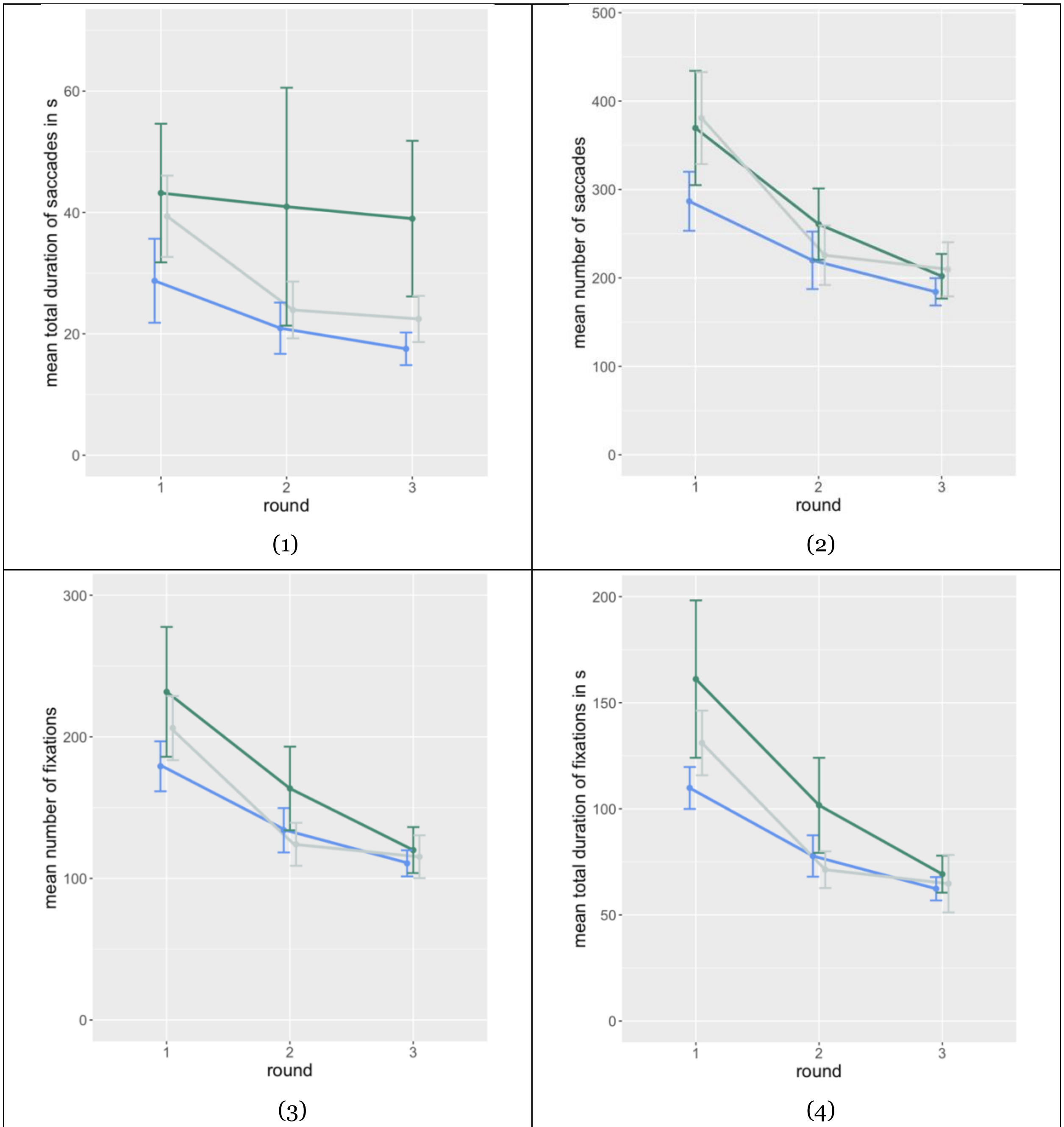


Figure 5. Changes in Eye-tracking Metrics, Duration of Saccades (1), Number of Saccades (2), Duration of Fixations (3), and Number of Fixations (4) over the Three Learning Rounds. Metrics for AR with Visual Guidance (blue), AR without Visual Guidance (green), and Paper Instruction (grey)

Task Completion Time

Considering only the actual production process (exclusion of waiting times since they may vary due to the transportation system in the learning factory), participants with visual guidance needed 7 minutes and 1 second for three production rounds. Those without visual guidance required 7 minutes and 54 seconds, around 11.8% longer than those without. Those who learned with paper instructions needed 8 minutes and 11 seconds, around 15.4% longer than AR with visual guidance.

Discussion, Implications, and Future Research Agenda

Building upon the existing discourse regarding whether AR provides added value to work and learning processes or serves as an additional source of cognitive load, the present study contributes to this debate by exploring how specific designs of AR can mitigate cognitive load during usage. To address this objective, this paper uses visual guidance, such as arrows and frames, to design AR that cognitively supports rather than overwhelming the learner. It also tests the design compared to AR without visual guidance and paper instructions. Additionally, we focus on eye-tracking to gain insights into cognitive load changes, especially during work and learning. We employ a multifaceted approach encompassing both questionnaire-based assessments and eye-tracking as a physiological measurement tool to monitor temporal variations. The following chapter discusses the results against the background of the two research questions and derives implications for research and practice.

Using visual guidance in AR applications mitigates the perceived cognitive load in a work and learning task

Using AR or paper instructions affects participants' time to complete the production process. Interestingly, participants using AR without visual guidance needed 12% more time to complete the task and using paper instructions took 15% longer than using AR with visual guidance. The longer times may indicate that people need more time to find the relevant information and to link the information to the appropriate places in the work process. Moreover, people who use paper instructions must also integrate the relevant information spatially, as it is fixed at the edge of the field of vision. Furthermore, our findings also show differences between the groups based on the cognitive load questionnaire. The questionnaire data show that participants who use the AR application with visual guidance, like highlights on essential information, report a significantly lower cognitive load than those using AR without visual guidance or paper instructions. This supports our research hypothesis that using AR with visual guidance mitigates the perceived cognitive load during AR usage. We assume that providing arrows and frames on necessary parts helps the learner lead, which causes less unintended gaze switching between the work area and the instructions. Our findings align with previous research in the context, like the instructional theory from Mayer (2024). The Cognitive Theory of Multimedia Learning, partly based on Sweller and colleagues' (2019) Cognitive Load Theory, provides principles for designing learning material. Signaling recommends using cues, highlights, and frames for learning instructions, which is investigated in the context of learning but only sparsely investigated in AR. Bautista and colleagues (2023) performed an extensive literature review on “Strategies to reduce visual attention changes while learning and training in extended reality environments”. They reported the benefits of visual features for guiding attention to relevant elements, e.g., using similar colors and shapes to mark related aspects. Our findings supplement the findings in the context of learning with AR and emphasize adequate technology design based on cognitive load theory by drawing attention to essential elements.

Does the Integration of Visual Guidance in an AR Application Affect Cognitive Load Measured with Eye-tracking?

The eye-tracking metrics throughout the process show significant differences between the three learning rounds since saccades (number and duration) and fixations (number and duration) decrease. We interpret the significant decrease as learning progress throughout the three learning rounds. Therefore, participants need less time to process the various input sources. This aligns with previous studies by Bläsing and Bornewasser (2021) and Zagermann and colleagues (2018), which have demonstrated an association between durations of fixations and saccades to task complexity and cognitive load. Our findings indicate that people’s cognitive load decreases throughout the learning rounds. Interestingly, people learning with AR without visual guidance show a more extensive duration of saccades over all three learning rounds. The number of saccades and the number and duration of people's fixations are higher in learning rounds 1 and 2 and only equalize to that of AR with visual guidance in learning round 3. That provides a more nuanced view of the cognitive load and enriches the questionnaire data. Participants using AR with visual guidance exhibit reduced saccadic activity (decreased number and duration of saccades) in learning round 1, indicating that people benefit from additional guidance, especially during the early stages of learning. We interpret the data as visual guidance that mitigates cognitive load by providing further information and structure, supported by a decreased rate of saccades for people using AR with visual guidance in contrast to a higher rate of saccades for people using AR without visual guidance. In sum, the eye-tracking data suggest that people with no previous experience, in particular, benefit from stronger orientation and guidance in the form of visual cues (arrows and frames) at the start of learning.

Practical Implications

We derive three practical implications from our findings that guide the design of AR for work and learning purposes. Building upon the existing discourse regarding whether AR provides added value to work and learning or serves as an additional source of cognitive load, this paper offers a nuanced view of the issue. First, regarding the time needed to complete the task, our data show the benefits of using AR over paper instructions. Secondly, to mitigate cognitive load during work and learning tasks, we stress the need for meaningful AR design, which we integrate using visual guidance. Our study provides arguments for investing in a meaningful design since the questionnaire and eye-tracking data show that visual guidance is beneficial for balancing the cognitive load. Looking more specifically into the data, our findings also support previous research findings that AR does not automatically benefit cognitive load compared to paper instructions since the questionnaire data show no difference between AR without visual guidance and paper instructions. Moreover, when using AR without visual guidance, participants require more extended processing than paper instructions, which indicates a higher number and duration of fixations. However, this is reversed using visual guidance since the eye-tracking data and completion time suggest that participants using AR with visual guidance need less time to locate and process the information relevant to the subtask. This is shown by the reduced number and duration of saccades and fixations when using AR with visual guidance. Third, our findings suggest the benefits of adapting the information presentation in AR. Since our research finds differences in fixations and saccades during the initial learning, the metrics converge as the learning process. We emphasize research to investigate the extent to which visual support can be gradually reduced as learning continues.

Limitations and Future Research

Some limitations emerged in our study. Firstly, the task participants had to solve showed relatively low complexity, as revealed by the cognitive load data from the questionnaire. We aimed to keep the complexity low and enable everyone to understand the production process to complete the tasks. However, with higher complexity, differences in cognitive load between the groups would have been higher for both the questionnaire and eye-tracking data. At the same time, we are fascinated by the added value of visual guidance, which also has an effect with low complexity. If we think of highly complex environments, we expect even greater added value from AR applications with visual guidance. Compared to paper, AR enables people to display information in an integrated way in the work process, leading to less gaze switching between the work area and the instructions. We plan to transfer the application to a more complex application scenario in which AR-specific advantages such as 3D visualization will be further beneficial. The HoloLens 2 enables non-invasive integration of eye-tracking metrics within an AR HMD, facilitating real-world application and analysis. However, a second limitation emerges from the characteristics of the HoloLens 2. The sampling rate of 30 Hz may not be sufficient to capture and reproduce rapid eye movements or changes adequately. Especially in the design of adaptive systems, the sampling rate can affect the accuracy of the adaptation. However, since we are not in safety-critical areas (e.g., autonomous driving) but in the context of learning, we continue to see good opportunities to achieve meaningful results with the sampling rate. The eye-tracking framework used for the HoloLens enables the measurement of saccades and fixations on integrated AOI. Both metrics showed differences in response to the learning progress. However, future research would benefit from integrating additional eye-tracking metrics since research showed, e.g., the value of pupil dilation to predict cognitive load (Kosch et al., 2018; Shojaeizadeh et al., 2019). Lastly, since we envision gaining insights for developing adaptive AR *learning* applications, we intend to integrate long-term effects on learning performance and transfer into the experimental design. We suggest an adaptive system would benefit from a multifactor framework that integrates cognitive load and learning performance (e.g., learning content transfer and application).

Our findings reveal that providing guidance and orientation, especially at the beginning of learning, mitigates cognitive load. In further studies, we dive deeper into opportunities to provide individualized learning instructions with AR. Therefore, we intend to use the findings on eye-tracking to measure cognitive load and duration of learning exposure to develop adaptive AR applications based on the individual cognitive load (also see Bläsing & Bornewasser (2021)). Notably, our research used the non-invasive integration of eye-tracking metrics within an AR HMD framework, facilitating real-world application and analysis. Multiple applications use eye-tracking to detect cognitive load in response to different task complexity. However, most studies are applied in laboratory settings, controlling for input such as light or sounds. Our analysis suggests the applicability of using eye-tracking in a natural scenario.

Besides concentrating on learning performance, we aim to encourage other researchers to investigate human factors in AR design experimentally in future research. Despite the proliferation of various AR applications, developing precise design guidelines that integrate human factors, like cognitive load, still needs to be improved. Since many AR applications emphasize technological implementation, however, review articles (e.g., Buchner et al., 2021; Çeken & Taşkın, 2022) show that recommendations based on experimental comparisons are very rare, motivating the IS and HCI research community to provide more evidence to help design AR technologies.

Conclusion

This research explores how visual guidance in Augmented Reality (AR) influences cognitive load, task completion time, and eye movements in a work and learning task. The aim of this research is twofold: a) to investigate the value of using visual guidance to mitigate cognitive load arising from AR and b) to integrate eye-tracking metrics to gain a holistic understanding of participants' responses using AR in a work and learning setting. Our findings show that integrating visual guidance, like arrows and frames highlighting essential aspects of learning, mitigates cognitive load when using AR. Questionnaire data reveal that participants using AR with visual guidance report less cognitive load than those using AR without visual guidance or paper instructions. Moreover, the eye-tracking metrics depict fewer saccades and fixations, especially at the beginning of the learning for participants using AR with visual guidance. Our findings suggest that visual guidance supports the orientation and processing of new information. Furthermore, our research indicates the feasibility of integrating eye-tracking into AR HMDs to detect changes during learning in a real-world context to enable real-time adjustments to information presentation based on the measurement of cognitive load in the future. We posit that individuals undergoing the learning process exhibit improvement over three learning rounds, a progression that is evidenced by our eye-tracking data.

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