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Investigating the Use of Augmented Reality and Machine Learning in Electrical Engineering Courses

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Research Paper

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Abstract. The use of augmented reality (AR) in education and training is growing increasingly. However, applications to integrate augmented reality learning content into training for basic electrical engineering courses are scarce. The individual learning objectives of trainees complicate the digitalization of learning content, particularly for the drawing of circuit diagrams. To increase trainees' learning outcome while simultaneously relieving instructors of classroom supervision, we designed and developed an AR-based prototype, to enhance hand-drawn circuit diagrams in vocational training. The context sensitivity is achieved by combining AR with image recognition. In an experiment with twelve participants, a positive impact of the prototype on trainees' learning outcomes was observed, in comparison to a control group that received instructions without the prototype.

Keywords: Augmented Reality, Vocational Training, Circuit Diagrams, Object Recognition.

1 Introduction

Scientific research in the domain of vocational education and training (VET) shows that the use of augmented reality (AR) can offer learning advantages, compared to books or desktop computer applications (Garzón *et al.*, 2019; Radu, 2014). By using AR in VET, it is possible to enhance the learners' motivation as well as the learners' understanding of the presented learning materials (Li *et al.*, 2011). Especially in practice-oriented training, AR devices can support knowledge transfer and prepare learners for complex tasks (Buehler & Kohne, 2020). Numerous studies on the combination of AR with pedagogical approaches, such as situated or collaborative learning, indicate a positive impact on learning outcome (Garzón *et al.*, 2020). In a three-year consortium research project, we have examined the use of AR in an electrical engineering course. Electrical engineering is a discipline in VET, in which trainees learn the basics of electrical equipment, devices, and systems. Drawing circuit diagrams is also part of the curriculum. The diagrams allow to uniquely determine the dependency relationships between the different symbols of the circuit (Pando Cerra *et al.*, 2014). The training sessions examined in the research project are part of a mandatory three-week course for technical apprenticeships in the company. The trainees independently draw a two-way circuit diagram. As the trainees do not have knowledge about circuit diagrams beforehand, the task can be challenging. Going through the provided workbooks is time-consuming and the abstract concepts in workbooks often lead to a mismatch between theory and practice among students and trainees (Wang, 2016). Consequently, the transfer of specialized knowledge to the real application context in the course requires frequent assistance from the instructor. However, most of the instructor's time is spent correcting drawings rather than assisting individual learners. The instructor has little time to focus on individual trainees. Hence, during a meeting with the instructor, we defined the objective to reduce personal support for checking hand-drawn circuit diagrams and to increase the learning outcomes of trainees by a use of an AR-based application.

The digitization of hand-drawn circuit diagrams proved to be advantageous, enabling virtual interaction with teaching content and dynamic representation (Lakshman Naika *et al.*, 2019; Liu *et al.*, 2020), as well as simplified analysis of relationships (Dey *et al.*, 2021). Existing AR-based solutions for circuit symbol recognition rely predominantly on computers (Abdel-Majeed *et al.*, 2020; Bhattacharya *et al.*, 2020; Dewangan, 2018) or smartphones (Hernández Mesa *et al.*, 2017). However, a significant drawback of these approaches is that the creation of sketches is interrupted by the need to capture images and switch to the respective device, impeding the learners' workflow. The goal of this contribution is to provide trainees with context-sensitive augmentation through AR glasses. The underlying research question is: How augmented reality (AR) can support training sessions in electrical engineering courses within the framework of hand- drawn circuit diagrams? By using an AR based application, we try to achieve a more immersive and independent learning experience for the trainees.

To generalize the results, we discuss the design and evaluation of the prototype to facilitate the transfer of the results to future prototypes that support hand-drawn learning activities. But first, in the following section two, the current state of research regarding AR and artificial intelligence (AI) in electrical engineering education is presented. The third section provides a description of the applied Design Science Research (DSR) method and related research. In the fourth section, the derived requirements for an AR-based application are described, along with the subsequent translation of these requirements into a prototype which uses AI-based object recognition to identify hand-drawn circuit symbols. The application was subsequently evaluated for learning outcomes in a regular training session through a quantitative study. The results of the evaluation are shown in chapter five. The discussion of the findings is presented in section six, followed by the conclusion in section seven.

2 Related Work

VET aims to equip students and trainees with skills and competences but require continuous adaptation towards new technological developments (Kazancoglu and

Ozkan-Ozen, 2018). The spatial virtual representations provided by AR devices can be used in VET to convey three-dimensional learning materials (Radu, 2014). The digital extension of the real environment with virtual content in real time is the fundamental characteristic of AR (Vogel *et al.*, 2020). A literature review by Avila-Garzon *et al.* (2021) identified a total of 3475 studies on educational context related to AR between the years of 1995 and 2020, demonstrating the relevance of AR in VET. Numerous other studies in the educational field concluded that AR learning materials can be effective in increasing the learning outcome for students (Ibáñez and Delgado-Kloos, 2018; Radu, 2014). AR can effectively reduce the occurrence of misconceptions in subjects that involve spatial relationships, which are often difficult to comprehend, by making complex concepts more accessible and understandable.(Ozdemır *et al.*, 2018; Sirakaya and Cakmak, 2018). It is also broadly used in natural sciences, mathematics, and statistics (Garzón *et al.*, 2019; Li *et al.*, 2011). A commonly used pedagogical approach in the field of AR is the theory of situated learning, which refers to AR training materials in authentic environments (Garzón *et al.*, 2020).

In a review by Radu (2014), 26 empirical studies in education were analyzed to compare AR with non-AR applications. Most of the studies of the review indicate that AR applications lead to positive learning outcomes for students in compare to media such as books or desktop computers. It is shown that learning content stays longer in memory and information can be transferred more efficiently to physical tasks (Radu, 2014). However, further evaluations of AR applications in education are still needed (Garzón *et al.*, 2019; Saltan & Arslan, 2016; Wu *et al.*, 2013), e.g., regarding the optimal presentation of information (Phon *et al.*, 2014). When measuring the learning outcome, different parameters are used in the literature: e.g., the completion time for the task, the number of mistakes made, perceived feedback, and a pre-post-test design with questions about the learning content. However, the completion time for the task or the number of mistakes made, are not sufficient measurement criteria for the learning outcome. They do not provide information if learners gained an understanding of the performed task (Wuttke *et al.* (2022).

Current research emphasizes the need to further explore AR in VET to facilitate a better understanding of learning materials among trainees (Hernández Mesa *et al.*, 2017; Liu *et al.*, 2020). In the VET field of teaching circuit diagrams, instructors bear the responsibility of correcting hand-drawn circuit diagrams made by learners and providing subsequent feedback on the individual drawings. This tedious process can be streamlined by employing automated recognition of diagrams and digital verification of logical correctness (Lakshman Naika *et al.*, 2019).

In addition to AR, AI is already being employed in VET to address domain-specific challenges across a wide range of applications (Chen *et al.*, 2020; Goksel and Bozkurt, 2019; McArthur *et al.*, 2005; Yang and Bai, 2020). The recognition of objects in a camera stream is one of the key topics of AI. In non-VET applications, recognition of circuit diagrams is used for digitizing concept drawings (Liu & Xiao, 2013; Pravalpruk & Dailey, 2016). The topic of object recognition is highly coupled with another key topic of AI: Machine Learning (ML). Through ML, new (artificial) knowledge is derived from empirical data and used for future predictions or decision making (Ongsulee, 2017; Provost & Kohavi, 1998). The methods currently used by AR applications to capture, analyze, and interpret incoming information are still dominated by traditional, non-AI approaches, but can be significantly improved through the use of AI (Sahu *et al.*, 2021).

3 Research Approach

The research in this paper is conducted according to the DSR method of Peffers *et al.* *(*2007). With this DSR method, the complete process from the definition of a problem to the evaluation of a corresponding artifact and the discussion of the results can be performed systematically. Hence, it provides a consistent and clearly structured approach to develop IT artifacts. The six phases of the selected DSR method are shown in Figure 1.

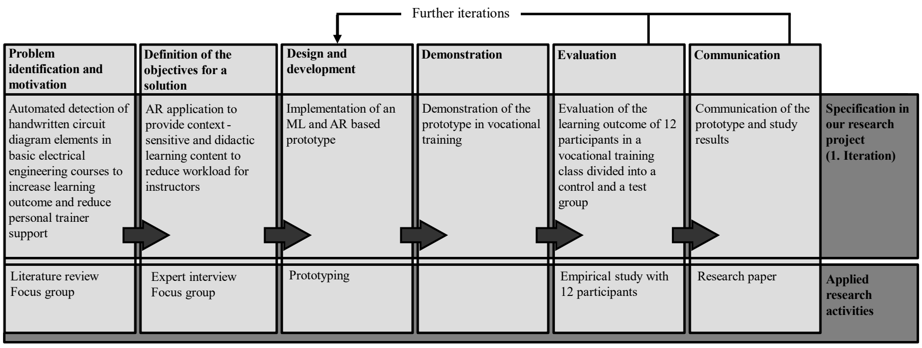

Figure 1. DSR activities adapted from Peffers *et al.* (2007).

The DSR described in this paper started with the selection of use cases at two companies and two vocational schools that took place in a three-year consortium research project. Within the project, we are aiming to integrate AR into the curricula of vocational schools and companies. The investigation of the use cases have been conducted to support instructors and create innovative educational opportunities (Dreesbach *et al.*, 2021). A focus session with all project partners at the beginning of the research identified four distinct scenarios for the application of AR. The investigated use cases comprise the familiarization with a woodworking center and the configuration of servo motors in the two vocational schools. In the two companies they include the manual assembly of an air conditioning module as well as the design and development of a two-way circuit.

The design and development of a two-way circuit is part of a basic electrical engineering course and takes place at a market-leading German manufacturer of semi-finished copper products. We identified the need for automated recognition and verification of handwritten circuit drawings (problem identification and motivation). Within the company-specific training, the basic electrical engineering course is mandatory for industrial mechanics, machinists, materials testers, and process engineers. As a part of this basic course, trainees learn how to plan, draw, and assemble an alternating circuit. Firstly, the necessary equipment is explained, and the trainees must answer theoretical questions about it. They have to find the answers to these questions independently, either from books or provided spreadsheets. Then the instructor specifies the necessary equipment for the assembly of an alternating circuit. For each type of equipment, the corresponding circuit symbol is presented and discussed. Then, in the following lesson, the trainees must draw a circuit diagram for the alternating circuit. While drawing, they are supported by the instructor, who answers arising questions and checks the progress of the drawings. More precisely, the instructor checks the selection and correct representation of the circuit symbols as well as the line thickness. So far, the drawings are done with the use of pen and ruler.

Based on the identified need for an automated recognition and verification of handwritten circuit drawings, we conducted a systematic literature review to identify related work. According to Cooper's (1988) definition, a literature review is intended to be a complete and selective coverage of the knowledge base in order to find research results on practical applications. We used the following search term and its German equivalent, too: *(("Circuit Symbol*" OR "Electr* Symbol*" OR "Circuit Diagram*" OR "Electrical Diagram") AND ("*recogni*" OR "*detect*" OR "identificat*" OR "classificat*") AND ("hand-drawn" OR "handwritten" OR "sketched"))*. We screened the databases Springer Link, IEEE-Xplore, Wiley Online Library, Elsevier Scopus, and Elsevier ScienceDirect. We performed a forward and backward search and removed all duplications (Vom Brocke *et al.*, 2009). The results were checked for (1) implementations, with particular emphasis on (2) prototypes that were implemented and utilized in lessons. Papers were sorted out largely according to the procedure of Vom Brocke *et al.* (2009) based on titles, abstracts, and finally on text content. After filtering, we came across seven research papers that addressed the digital support for students or trainees while drawing circuit diagrams.

The implemented prototypes found in literature pursued different objectives and can be subdivided into prototypes that used paper and those that used a digital tablet for the drawings. Lakshman Naika *et al.* (2019) used 1000 images of hand-drawn circuit symbols from nine different classes to develop a circuit symbol recognition algorithm and combined it with a finite state machine to recognize the type of circuit. The proposed method leads to over 99% overall accuracy. Dey *et al.* (2021) also investigated the prediction accuracy of hand-drawn circuit symbols on paper. They evaluated a two-stage neural network and an extended training dataset for recognizing circuit symbols on paper. The two-stage neuronal network achieved significantly more accurate predictions than a single-stage neural network (Dey *et al.*, 2021).

The tablet-based prototypes developed by Valois *et al.* (2001) and Ejofodomi *et al.* *(*2004) recognized hand-drawn circuits and their symbols on the tablet and presented them in a graphical form afterwards. With the developed prototypes of Liwicki & Knipping (2005) and Liu *et al.* (2020), learners also draw circuit symbols freely on a digital screen. Furthermore, these applications include a linked virtual simulation of the recorded circuit symbols. Hernández Mesa *et al.* (2017) developed the prototype "ElectAR" to support basic electrical engineering courses, a smartphone-based application for the recognition and AR-based enrichment of circuit symbols. With ElectAR, students capture circuit symbols on a sheet of paper with the smartphone camera. The application extends the symbols with subject-related learning content (Hernández Mesa *et al.*, 2017). However, the learners do not draw the circuit themselves. Instead, prefabricated drawings are overlaid with learning content in the form of images, videos, and texts. These contents describe how each component of the circuit works in detail (Hernández Mesa *et al.*, 2017). We did not encounter papers that evaluate prototypes designed to support hand-drawn circuit diagrams in VET.

In the second step of the DSR (definition of the objectives for a solution), we established the design and necessary functionalities of the prototype. Therefore, we talked to the instructor of the basic electronics course in a guided interview. The instructor was considered an expert because of his relevant knowledge in theoretical and practical training (Liebold & Trinczek, 2009). He has been teaching the basic electronics course for five years that includes the drawing of electrical circuit diagrams. The interview lasted 30 minutes and covered the relevance of the problem, the current state of the lesson, potential measures, and environmental factors. In accordance with the qualitative content analysis of Kuckartz (2018), the recorded interview was transcribed, content categories were abstracted, and statement frequencies per content category were documented. The abstracted content categories included the problem relevance, target group, procedure of the training unit, circuit symbol types, teaching content, and the tasks of the instructor. Based on the interview results, the interviewing researcher developed requirements for the AR application. In a following step, he then initiated a focus group to discuss the requirements with two other researchers from the fields of computer science and augmented reality to compare the developed requirements with the results of the literature review. In a moderated discussion he presented each of the requirements to the focus group. Afterwards, the implementation of the prototype started as the third phase of the DSR (Design and Development). Then, the demonstration of the prototype in the basic electrical engineering course was conducted in the fourth phase of the DSR (Demonstration). In the fifth phase of the DSR (Evaluation), we tested the prototype with twelve trainees from the course, in a study with a between-subjects design as described in section 5.

4 Prototype Development

4.1 Consolidation of the Requirements for the Prototype

The focus group in the second step of the DSR consolidated the findings from the expert interview and the literature review, consequently determined the design and functionalities of the AR prototype to support basic electrical engineering courses. In total, three functional requirements (FR) and one non-functional requirement (non-FR) for the development of AR learning elements were collected.

The trainees were already familiar with the circuit symbols required for the drawing, as they had been introduced to them in a previous lesson. The required symbols are as follows: the four symbols luminaire, socket, junction box with fuse, and changeover switch. The first requirement for the prototype is that the AR-based supplements for the symbols shall contain the instructional content from the regular electrical engineering course (**FR 1**). The content includes the details of the functions of the components, examples of specific use-cases, a reference image, and a statement of information about the connection marking of each symbol, completed with a checklist of inspection points used by the instructor. Since the symbols drawn by trainees may contain minor errors in the representation, the second requirement is that the prototype considers correctly drawn circuit symbols as well as those that contain minor errors (**FR 2**). However, it was clear from the interview with the instructor that the prototype should not explicitly illustrate the required circuit diagram drawings. Instead, the trainees should plan the drawing on their own, select necessary circuit symbols, and sketch them on a blank sheet of paper before the AR-based verification and support becomes active. Once they completed the drawing, the prototype should provide context-sensitive supplementation to verify the results (**FR 3**). In addition to the three FRs, the interview also revealed one non-FR. The application should be intuitive for trainees to use (**non-FR 1**).

As part of the electrical engineering course, the instructor asks the trainees to draw the lines between the circuit symbols after they correctly drew the four circuit symbols. To keep the implementation effort low for the first iteration in the DSR, the focus group initially did not consider the evaluation of the lines between the symbols. A computer-based prototype developed by Agarwal *et al.* (2017) can recognize the lines connecting them in addition to the individual circuit symbols, but in this prototype, too, the circuit symbols are first extracted from the image (Agarwal *et al.*, 2017). The focus group was followed by the prototype development and a study together with the instructor.

4.2 Model for Object Recognition of Circuit Symbols

We performed an ML-based object recognition during prototype development, so that the AR device recognizes the four symbols required for the circuit diagram to meet FR 1. The trainees themselves created the training dataset by drawing the circuit symbols by hand on a white DIN A4 paper. In total, the trainees and the instructor created fifteen sketches for the dataset. Ten of the sketches contain correct circuit symbols. The other five sketches were intentionally prepared in such a way that they contain common mistakes, such as missing or incorrectly drawn components, to include incorrectly drawn symbols in the training data set (FR 2). We took 317 photos of the sketches with different distances and angles using a 25-megapixel camera. Light sources and backgrounds also varied. Subsequently, we labelled all pictures.

After creating the training dataset, we undertook a one-hour training of the model for object recognition using Microsoft Custom Vision. We exported the model to the Open Neural Network Exchange (ONNX) format. ONNX is an open format for representing ML models. The threshold for the probability of a correct prediction (Probability Threshold) is 50%. The model marks predictions that have probability equal to or greater than 50% as correct forecast. It considers all other predictions incorrect. The overlap threshold, which was 30% in our use case, is the value that indicates that the model considers a prediction correct only when the bounding box of the prediction overlaps at least 30% of the actual bounding box stored in the training dataset. When training the model, we aimed for high ratios of the values because of the potential degradation of these values when running the model on HoloLens 2 due to the restrictive computational resources of the processor and graphics card. The precision of it, which indicates the overall performance of the object recognition for all labels (Henderson & Ferrari, 2017), is 97.1%. The recall, in our use case 97.1%, is the value that indicates that 97,1% of the actual recorded circuit symbols are correctly recognized by the model (Powers, 2011). To conclude, the mean average precision of 99.1% indicates the overall performance of the object recognition for all labels (Henderson & Ferrari, 2017). For the present use case, we judged the evaluated metrics to be sufficient for the recognition of hand-drawn circuit symbols, as all values are in the high upper percentage range.

The two Unity-compatible frameworks Unity Barracuda and Windows Machine Learning (WinML) were available for running the trained model on HoloLens 2. We compared the two frameworks using statistics performed by Lazar (2021). Unity Barracuda computational performance is significantly faster than WinML because it uses the HoloLens 2 graphics card for computation, whereas this is not yet possible with WinML (Lazar, 2021). However, Barracuda requires additional pre-processing steps to the training model. This includes processes such as cropping, scaling, and normalization of the images captured by the HoloLens 2 camera. We used the WinML framework v19041 for the prototype to be able to import the trained model into Unity without further modifications.

4.3 Graphical User Interface

We developed the elements of the graphical user interface (GUI) in the Unity 3D development environment in conjunction with the Microsoft Mixed Reality Toolkit framework. To implement the non-FR of intuitive operation of the application, all menu windows have the same structure and recurring elements appear at the same positions. They also have a header that bears a textual title and describes the contents of the respective window. The title background is additionally colored purple to distinguish it more strongly from the other contents of the environment. A button in the header allows back navigation to the previous window and a menu provides structured navigation. In addition, it is possible to reach into the header of a window to reposition the respective window with a hand movement. The user can adjust the size of the window by grasping a corner and making a diagonal hand movement. Below the header of a window the different contents are displayed. When starting the prototype, a sliding button allows the trainee to take a picture of their circuit diagram. The prototype performs object recognition with the help of the trained model and identifies the four circuit symbols for the electrical engineering course (FR 1). After a symbol was identified, it provides a menu that obtains more information on the recognized symbols. The trainees can select one of the circuit symbols to view the associated information. Figure 2 shows the GUI elements after the AR application recognized the symbol of a socket. The GUI provides a checklist, and a reference image of the socket. The checklist includes the inspection points used by the instructor in the regular training session to support the learner with some hints in a checklist on how to draw the symbol correctly. Therefore, the trainees can themselves perform the verification for each of their hand-drawn circuit symbols (FR 3).

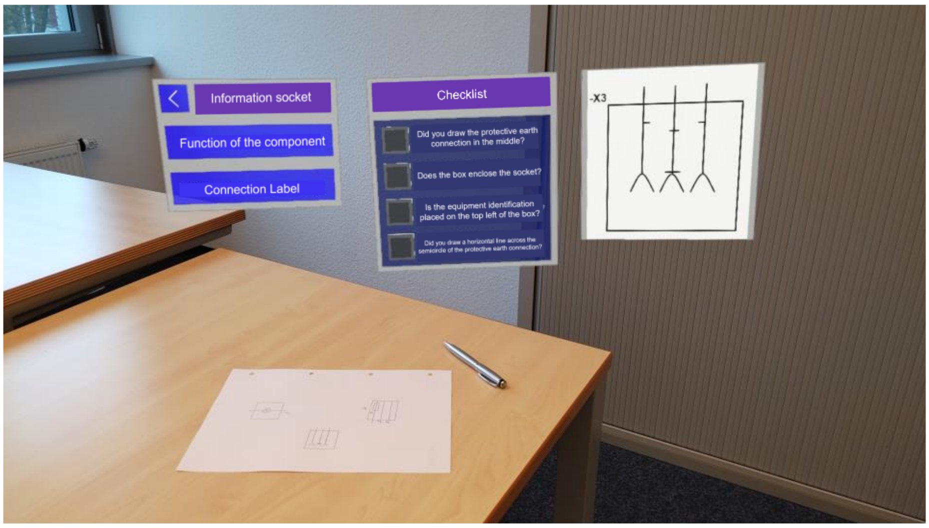

Figure 2. GUI elements for the checklist and a reference image of the socket (translated)

The learners can select a second menu option, where a text box provides examples of specific applications for the circuit symbol. If the trainee checks off all the boxes on the checklist regarding the identified circuit symbols, a success message appears.

5 Prototype Evaluation

To evaluate the prototype, we conducted a study as a pre-post-test design with a total of twelve trainees from different training areas (industrial mechanics, machinists, materials testers, and process engineers). We paid special attention to creating a realistic setting and adopting a structured approach for our evaluation. This allowed us to explore the feasibility of the implemented features in our AR prototype and gain a deeper understanding of the developed design, despite the limitations of our small sample size. Up to this point, all participants haven't previously taken any other modules in the field of electrical engineering in their respective training programs. All trainees completed a multiple-choice questionnaire (MCQ-1) at the beginning of the study, which included 21 knowledge questions of varying difficulty about the mechanisms and operating equipment of a two-way circuit. The questionnaire was prepared in advance by the instructor according to the learning materials. The treatment afterwards includes the recording of a two-way circuit. For the treatment trainees were randomly separated into two groups with one group using the developed AR prototype and the other group using the conventional workbooks of the training session to acquire the necessary expertise. The group without prototype support was directed by the instructor to draw a two-way circuit while the instructor was available to address any questions arising. This setup remained consistent with the previous course instruction and undergo no further modifications. The other group was individually guided to enter the room. The instructor provided instructions on how to use the AR glasses, allowing for a brief trial period to become familiar with the device. Subsequently, the participants in the group were instructed to draw a two-way circuit. The individual session ended once the two-way circuit was completed, along with a final questionnaire. The entire evaluation process with the prototype took approximately 20 minutes per participant. Upon completing the task, participants in both groups were instructed to complete a clearly assignable multiple-choice questionnaire (MCQ-2), which asks the same questions as MCQ-1. The results taken from the group-specific MCQ-1 and MCQ-2, in the form of scores, were subsequently evaluated with a mixed ANOVA and used to measure the learning outcome.

As a precondition for the Mixed ANOVA, the Kolmogorov-Smirnov test showed that the data from the survey are normally distributed. Likewise, there are no outliers. The Levene test confirmed the equality of the error variances, and the Box test confirmed the equality of the covariance matrices. The alternative hypothesis H1 states a positive correlation between the use of the developed prototype and the total scores achieved in answering the MCQs by the participants in the study ($p <= 0.05$). To finally answer the research question posed in this paper the H1 is examined using the results of the Mixed ANOVA.

In the following, the measure of a potential interaction effect between time (before and after treatment) and groups (control group versus experimental group) is examined. Since there are no more than two measurement time points for the total scores, sphericity can be assumed. Therefore, the interaction between time and group is significant with a result of 13.412 for the F statistic ($F(1.0; 10.0)$ with $p = 0.004$). Thus, from the within-subjects effects tests for the interaction between time and group on the total score achieved, it appears that there was a statistically significant interaction with an effect size of 0.573 between time (before, $I = 1$; after, $J = 2$) and the two groups. Looking at time separately for both groups, it is noticeable that there was a statistically significant effect ($\eta^2 = 0.914$) of time on the total scores of the experimental group with the AR prototype (at $\alpha = 0.05$). Likewise, the F statistic for the experimental group with AR prototype shows significancy with a result of 52.826 ($F(1.0; 5.0)$ with $p = 0.001$). For the control group without AR prototype, there was no statistically significant effect of time on total score, as seen in the F statistics with a result of 0.741 ($F(1.0; 5.0)$ with $p = 0.741$).

The researchers calculated the pairwise comparison of the estimated marginal means by group and time. Accordingly, the significant effect ($p = 0.001$, at $\alpha = 0.05$) on the total scores of the experimental group arose from task processing (interval between $I = 1$ and $J = 2$) with the AR prototype. As illustrated earlier, there is no significant effect on the total scores of the group without the AR prototype. In the pairwise comparison for the time points before and after task processing, the significance ($p = 0.741$) for the group without AR prototype is above the reference level of $\alpha = 0.05$. Based on the statistical analysis, the alternative hypothesis H1 is accepted because of a positive relationship between the use of the developed prototype and the total scores achieved in answering the MCQs by the participants of the study.

Following the evaluation sessions, the prototype received overwhelmingly positive feedback from participants. The prompt presentation of didactic content coupled with the interaction with virtual elements during circuit symbol recording was deemed exciting. The results indicate that it was beneficial to design the prototype in a way that allows trainees to draw an individual circuit diagram on their own and illustrate the results afterwards using the AR glasses. This approach is consistent with the constructivist perspective that leaves room for learners to actively build their own expertise (Shuell, 1986). Furthermore, the design of the prototype including a checklist and an illustration of the detected circuit symbol to verify the drawing, was adequate for the study and showed promising results.

6 Discussion

A demonstration of AR applications as in our DSR is important to evaluate the use of AR in education and to further discuss the existence of significant benefits (Garzón *et al.*, 2019; Saltan and Arslan, 2016; Wu *et al.*, 2013). The conducted study indicates a positive learning outcome for the AR application. The trainees who used the AR prototype in our study were able to achieve a higher score in answering the questionnaire on the basics of a two-way circuit, than those who used the conventional learning materials. Due to the use of AR glasses, the trainees can easily compare the learning materials displayed with their drawings. By having both hands free, they can also easily make changes to their drawings during the review. Therefore, the results from our conducted study support the findings of Hernández Mesa *et al.* (2017) that AR applications in circuit diagram drawings have an advantage over previous teaching methods.

Based on the results of our research, the intended reduction of the workload for the instructor was not initially achieved by the prototype. This is due to intensive support provided during the presentation of the AR glasses and familiarization of the trainees. Towards the end of the study, the trainees knew the relevant forms of interaction with the AR glasses. Therefore, their familiarization time for future applications is reduced. However, the company benefits because AR devices are increasingly finding their way into professional practice and trainees are introduced to the technology at an early stage through the prototype. Our impression during the implementation of the study was that both technological knowledge and acceptance towards AR were promoted among the trainees through the application. The positive learning outcome and the successful combination of AR and object recognition indicate a transferability of our results to other use cases, such as assisting with the circuit assembly after the trainees have independently validated their hand-drawn circuit diagrams.

Our study includes three limitations. The first one is the limited scope of the prototype, which is restricted to the two-way circuit. However, through an already implemented interface for the extension of individual information and test points into the prototype, further content can be efficiently integrated in the future. The second limitation is the sample size of twelve trainees in total, which does not ensure general validity of the proven learning outcome. The third limitation is the absence of a supplementary study conducted at a later stage to investigate potential divergences in long-term learning outcomes between the two approaches.

At a technical level, further research can transfer the results to future prototypes that support hand-drawn learning activities. The training dataset created to recognize the drawn circuit symbols was able to achieve a high-performance result for the trained model. The full (offline) execution of the trained model using an ONNX model on HoloLens 2 achieved adequate results during the study. Similar use cases at the technical level could be the drawing of machine elements or physical drawings as well as support in the acquisition of written language for children or persons with low language skills or a writing disability. The results underline the use of an object recognition which considers both correctly drawn circuit symbols and those containing minor errors (FR 2). Nevertheless, one drawback of the prototype was sporadically evident during the study. The application does not provide indications when the trainees cannot replicate the required circuit symbols from the previous lesson or cannot replicate them sufficiently. In that case, the application does not recognize them. Accordingly, a hint function should be integrated into the application to support trainees in the event of start-up difficulties. Further research is needed regarding the dependency relations between the different symbols of the circuit. Due to the high number of possible solutions, a training data set for the dependency relations will be significantly larger.

7 Conclusion

Within the context of this paper, we designed and developed an AR-based prototype to enhance hand-drawn circuit diagrams in vocational training with supportive learning content. Two developers and an instructor, supported by relevant literature, defined the requirements of the prototype for didactic enrichment of circuit diagrams. The implementation of the prototype considered the established requirements pertaining to design and learning content. Following that, the prototype underwent training using AI-based object recognition to accurately identify hand-drawn circuit symbols. In a between-subjects study designed for learning outcome, the experimental group with the prototype was found to have higher learning outcome than the controlled group. The results from the evaluation of the developed prototype demonstrated the potential of AR to improve education and training in the field of electrical engineering. Considering that our research identified further work involving the demand and investigation of systems to recognize and verify hand-drawn circuit diagrams. The scientific relevance of the results are already evident in the first iteration of our DSR. The outcome of our study justifies further investigation to establish a practical use of the prototype in vocational education. In additional iterations of the DSR, the prototype should be more developed, especially with respect to the evaluation of the lines between the circuit symbols.

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