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Review

Using sensors and augmented reality to train apprentices using recorded expert performance: A systematic literature review☆

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ABSTRACT

Experts are imperative for training apprentices, but learning from experts is difficult. Experts often struggle to explicate and/or verbalize their knowledge or simply overlook important details due to internalization of their skills, which may make it more difficult for apprentices to learn from experts. In addition, the shortage of experts to support apprentices in one-to-one settings during trainings limits the development of apprentices. In this review, we investigate how augmented reality and sensor technology can be used to capture expert performance in such a way that the captured performance can be used to train apprentices without increasing the workload on experts. To this end, we have analysed 78 studies that have implemented augmented reality and sensor technology for training purposes. We explored how sensors have been used to capture expert performance with the intention of supporting apprentice training. Furthermore, we classified the instructional methods used by the studies according to the 4C/ID framework to understand how augmented reality and sensor technology have been used to support training. The results of this review show that augmented reality and sensor technology have the potential to capture expert performance for training purposes. The results also outline a methodological approach to how sensors and augmented reality learning environments can be designed for training using recorded expert performance.

Bloom and Sosniak (1985) investigated the childhoods of 120 elite performers and observed that all of them had practised intensively and trained with devoted mentors. Ericsson, Prietula, and Cokely (2007) have also emphasized the importance of experts as mentors for apprentices. While experts seem imperative to train apprentices to achieve superior performance, they are not free of shortcomings. Experts tend to underestimate how difficult a task can be for apprentices (Hinds, 1999). Experts are also often unaware of all the knowledge behind their superior performance (Patterson, Pierce, Bell, & Klein, 2010) and thus omit information that apprentices may find valuable (Hinds, Patterson, & Pfeffer, 2001). This may cause apprentices to find it difficult to learn from experts. Moreover, difficulty also lies in the shortage of experts to train apprentices in one-to-one settings (Bloom, 1984).

According to Ericsson, Charness, Feltovich, and Hoffman (2006), an expert is someone who consistently demonstrates superior performance in a representative set of tasks for the domain of his/her expertise. We use the term “expert performance” in the context of this paper to describe the performance of an expert. Representative tasks are structured and managed drills which elicit the same

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set of knowledge and skills that would be necessary in the corresponding real-world tasks. Representative tasks allow for the quantification of expert performance, which can then be analysed to assess its mediating mechanisms. This enables us to measure and capture performance, which can be used in various ways for training apprentices.

To train apprentices with captured expert performance data, we first aim to capture a rich representation of the expert performance using sensor technology. The reason to focus on sensors is that they have the capability to unobtrusively measure observable properties, which is ideal for capturing expert performance in representative tasks. Bower and Sturman (2015) have elaborated on the educational affordances of sensors and their potentials for training. A sensor is commonly defined as: "a device that detects or measures a physical property and records, indicates, or otherwise responds to it" ("Definition of sensors by Oxford Dictionaries", 2018). However, expertise is a much broader term which encompasses tacit skills that cannot be captured directly by sensors. Regardless, sensors have already been successfully used to train apprentices based on expert performance data (e.g. Jarodzka, Van Gog, Dorr, Scheiter, & Gerjets, 2013; Schneider, Börner, van Rosmalen, & Specht, 2017). These studies have relied on the manual encoding of recorded data between the capture and training phases. With this study, we aim to outline instructional designs which do not require manual encoding of sensor data. Moreover, technology such as augmented reality (AR) offers important affordances such as contextual awareness, which allows for the meaningful recording and use of sensor data by integrating the sensor data into the interaction (Guest et al., 2017), potentially reducing the manual phase between capture and training.

AR overlays the real world with virtual content to create an immersive platform which places the trainee in a real-world context, engaging all his/her senses (Bacca, Baldiris, Fabregat, Graf, & Kinshuk, 2014). Modern AR systems can communicate with various sensors in real time, which can offer a broad range of training affordances. We term such a combination of sensors and AR as "sensor-based AR" in the context of this paper. Sensor-based AR training environments can support apprentices by providing personalized guidance and feedback when experts are not available. Sensor-based AR environments also provide a rich multimodal and multi-sensory medium for apprentices to learn efficiently from expert performance data. While Bacca et al. (2014) suggested, based on their review, that sensor-based AR posits a rich educational potential for the personalization of training, Bower and Sturman (2015) have stressed the risk of putting technology before pedagogy. This is particularly true for emerging technologies, such as sensor-based AR, that provide a huge range of affordances which may or may not be beneficial for training and education. Therefore, to ensure we are guided by proper pedagogy, we structured our exploration of sensor-based AR with a pedagogical framework known as the Four Components Instructional Design (4C/ID) model. The 4C/ID model is a non-linear and systematic processing model for designing a complex learning environment (van Merriënboer, Clark, & de Croock, 2002). The basic assumption of the 4C/ID model is that all complex learning can be represented in a combination of four components described by the model (Van Merriënboer & Kester, 2014), namely:

1 Learning task: Learning tasks are authentic, whole-task experiences that are provided to apprentices to promote schema construction for non-recurring aspects of the task. Construction of mental models by the apprentice can be facilitated by observing or imitating the expert. For example, by first demonstrating examples of how a particular concept is used before tackling the problem, apprentices are provided with the opportunity to construct relationships between chunks of knowledge gained during observation and imitation.
2 Supportive information: Supportive information supports apprentices to deeply process new information for the construction of mental models. It provides domain-related information, such as approaches to solving problems rather than procedural information, to support the learning and the performance of nonrecurring aspects of the task.
3 Just in time information: Just in time information is the prerequisite procedural information to the learning and performance of recurring aspects of the learning task provided to the apprentice precisely when required. Procedural information is immediately diminished for the subsequent task to facilitate automation of the task.
4 Part-task practice: The last component of the 4C/ID model is the part-task practice, which recognizes that some parts of the task are automatic and recurrent. To automate recurring aspects of the task, it is necessary that apprentices practise these recurrent tasks repeatedly. Part-task practice items are provided to apprentices to promote rule automation for recurring aspects of the whole complex skill by means of "strengthening", in which cognitive rules accumulate higher strength upon repeated successful executions (Kirschner & van Merriënboer, 2008).

We selected the 4C/ID model as an appropriate framework to guide this study due to its potential to support training in complex skills, as well as due to its close resemblance to the underlying principles of deliberate practice (Neelen & Kirschner, 2016). McDaniel, Schmidt, and Hunter (1988), as well as Ericsson et al. (2006), found that only individuals who indulged in deliberate practice attained superior performance. Thus, practice should be deliberate, that is, aimed at improving that particular skill by reflecting on previous performance and collecting new experience. However, it is difficult to perform or maintain deliberate practice because it is cognitively demanding for the apprentice to be conscious of his/her own performance (Rikers, Van Gerven, & Schmidt, 2004). Expert mentors are crucial to support deliberate practice in apprentices (Ericsson et al., 2007). Deliberate practice requires one-to-one settings where an expert continuously provides guidance and feedback to the apprentice (Carey, 2014).

In conclusion, this literature study aims to investigate the potential of sensor-based AR to support deliberate practice in apprentices with the help of captured expert performance data. Therefore, we examine patterns in the literature that exploit the affordances of sensors for enabling the capture of expert performance. We also explore the use of sensor-based AR for training apprentices using expert performance data. As such we examine the following questions:

1. How can sensors be used to capture expert performance?

2. How can sensor-based AR utilize expert performance data to facilitate 4C/ID model-based training programs?

1. Methods

In order to explore how expert performance has been captured with sensors, we selected studies that either explicitly used sensors to capture expert performance or described systems which used manually-created expert models through task analysis. Similarly, we also chose studies describing systems that have the potential to use experts as a reference for training. To obtain relevant articles, we used the following criteria: we searched for the key words “Sensor”, “Augmented Reality”, “Training” and “Skill”. We observed that the use of the additional keyword “expert/expertise” delivered fewer results. The electronic databases included in this review were: ScienceDirect (Elsevier), SAGE, ACM and SpringerLink. We also addressed only recent studies (since 2014–2016), because AR and sensors are developing technologies that have seen a recent spike both in investments and funding since 2015 (“AR/VR Funding In, 2016 Already 85% Growth On, 2015”, 2016) and in maturity for mobile AR support. Only studies that provided an explicit description of their prototypes, the sensors they used and the objective of the prototype were selected for evaluation. Fig. 1 illustrates a number of different steps at which the articles were screened.

We examined the abstracts of 268 studies, which we identified among the initial search results from the keyword search. We evaluated these studies to check whether they met our inclusion criteria. Out of 268 studies identified, only a total of 78 studies, which were composed of 26 studies from SpringerLink, 2 studies from SAGE, 21 studies from ACM and 36 studies from ScienceDirect, were considered relevant.

After we had selected relevant studies, we first examined each of them in detail to understand how the authors had captured the expert performance. We identified studies that captured expert performance either using sensors or performing task analysis or both. No distinction was made based on the type of involvement of the expert, to facilitate the inclusion of papers that may not have used recent sensors to automate the capturing of expert performance.

While doing so, we also observed and clustered common instructional methods employed by the studies. Instructional Design Methods (IDMs) are learning design patterns that leverage expert performance to support training using sensors and AR. IDMs are built on the concept of capturing the expert performance and using it to train apprentices. IDMs are abstract from the domain, and from other factors such as the particular vendor sensors. These IDMs have been evaluated to test their abstractness from the domain with the experts in the context of a European research project, Wearable Experience for Knowledge Intensive Training (WEKIT).[1] The WEKIT project explores the potential of sensor-based AR to train apprentices in three different domains, namely: maintenance, medicine and astronaut training. The experts used to evaluate the IDMs were experts in the domain mentioned and are experienced trainers. To validate the abstractness of IDMs, we selected three representative tasks, one from each domain, and conducted task analysis with the respective experts to identify the knowledge and skills required to perform these tasks. Later, the experts were provided with a list of IDMs along with their descriptions and asked to select the IDMs that could be used to train the skills identified in this task analysis. The results showed that most IDMs are applicable across all three domains, which validates the claim that IDMs are applicable independent of the domain.

To further analyse these studies, we categorized these IDMs based on the four components of the 4C/ID model. Based on the assumption that all types of learning task can be represented in the form of the four components: 1) learning task, 2) supportive information, 3) just in time information and 4) part-task practice (van Merriënboer et al., 2002), we aimed to explore whether the sensors and AR are capable of supporting the 4C/ID model-based training approach with the help of expert performance. The results of the analysis are presented in the following section.

2. Results

2.1. Capture of expert performance

Sensors have the potential to capture various observable aspects of expert performance and the environment in which the expert performs. Some of these aspects may not be visible or obvious to the apprentice. Sensors can make invisible aspects of the task visible to apprentices, allowing them to achieve a better understanding of the process (Collins, Brown, & Holum, 1991). In addition, recorded expert performance data can be used to train apprentices, but it can also assist experts by enabling them to quickly create training materials while demonstrating. Apprentices have the opportunity to replay the expert's demonstration in a much richer manner while actually doing the task or, when needed, to learn from the demonstration. However, expert performance data can also be used for other purposes, such as providing formative feedback (Schneider et al., 2017) by using expert performance data as a benchmark. Sensor systems can also read and log apprentices' performance, which can allow an expert to keep track of an apprentice's progress, enabling the expert to provide feedback when needed. To incorporate such functionalities into a system, it is crucial to understand how sensors can be used to capture expert performance. Therefore, we investigated how sensors have been used to capture expert performance in the studies collected. From our analysis of 78 studies, we identified 25 studies that exclusively modelled the expert (classified as Task Analysis in Table 1) or used sensors to record the expert's demonstration of the task (classified as Demonstration in Table 1). We have summarized them in Table 1, which consists of 4 columns: The approach column defines the type of data that was captured, while the second column defines the types of sensor used. This distinction was made to ensure that our

[1] Wearable Experience for Knowledge Intensive Training: Project No 687669.

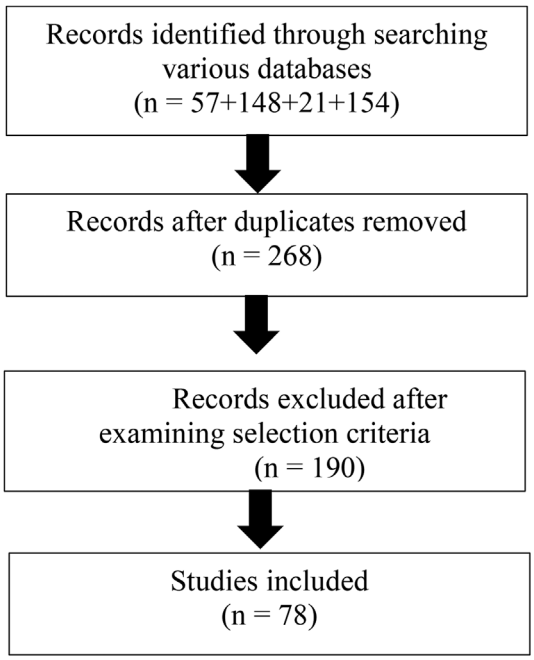


Fig. 1. Process of finding articles.

results were not confined by the type and vendor of the sensors. There can be more than a single type of sensor to capture a particular set of data; for example, different sensors can be used to measure stress levels. The table also includes the IDMs the authors used to exploit the recorded expert performance. The Studies columns lists the studies from the literature that implemented the approaches. Finally, the last column lists the type of IDM such recording approaches support.

2.2. Instructional design methods

We extracted the IDMs from the selected group of 78 studies. Our intention was to understand and document different IDMs that exploited the affordances of sensors and AR. We defined three general characteristics based on our observation of the implementation of IDMs, which are given in Table 2. Each IDM is characterized by a description, the unique features that define its implementation and the skill it can be used to train. The other characteristics include requirements for recording, such as hardware and software requirements, and for re-enacting by the apprentice, which may include wearable technologies. The list of questions is by no means exhaustive, as the IDMs are abstract from the domain, but using IDMs in the specific context typically leads to specializations. In addition, requirements for recording are not necessarily bound to the recording approaches found in the studies selected (see Table 1).

From our analysis of the selected 78 studies, we identified 18 IDMs. The studies and the IDMs they implemented are mapped in Table 3, along with the means and methods for capturing and enacting expert performance. Each IDM is identified by its self-descriptive name in the first column from the left.

After identifying all the IDMs, we further classified the IDMs according to the four components of the 4C/ID model in order to explore how sensor-based AR can be used to facilitate technology-enhanced 4C/ID learning environments. Evidence of the effectiveness of training environments designed in line with the specifications of the 4C/ID model for supporting deliberate practice in training contexts has also been documented by De Corte, for Research on Learning E. A.InstructionVerschaffel, Van Merriënboer, and Entwistle (2003) and Merrill (2002). In addition, Sarfo and Elen (2006) assessed technology-enhanced learning environments developed with 4C/ID specifications for expertise development and positively indicated that such systems have the potential to promote expertise development through deliberate practice.

2.3. Four component instructional design

The 4C/ID model is a non-linear and systematic processing model to design environments for complex learning. This model deals with complex skills by breaking down the complex task into sub-tasks without losing sight of the separate elements and the interconnections between them (van Merriënboer et al., 2002). The assumption of the 4C/ID-model is that all complex skills and their subskills can always be described in terms of four components, namely: 1) learning task 2) supportive information 3) just in time information, and 4) part-task practice. In the following section, we provide the results of the classification of the IDMs according to this framework. In addition, we have also mapped the type of attributes that the studies trained using the IDM.

Table 1
Capture of expert performance.

Demonstration of the task			
Approaches	Sensor used	Studies	Instructional Design Methods
Recording of body movement	- Infrared camera - Depth camera	- (Wei, Yan, Bie, Wang, & Sun, 2014) - (Khan, 2015) - (Prabhu, Elkington, Crowley, Tiwari, & Ward, 2017)	- Augmented mirror, - Formative feedback
Recording of hand movement	- Inertial camera - Infrared camera	- (Sun, Byrns, Cheng, Zheng, & Basu, 2016) - (Haug, Rozenblit, & Buchenrieder, 2014) - (Kowalewski et al., 2017) - (Ahmmad, Ming, Fai, & Narayanan, 2014) - (Kritopoulou, Manitsaris, & Moutarde, 2016) - (Zhao et al., 2016)	- Haptic feedback - Augmented path - Formative feedback
Recording of force applied	- Pressure sensor	- (Araki et al., 2017) - (Asadipour, Debattista, & Chalmers, 2017)	- Contextual information - Haptic feedback
Recording of focus areas	- Eye tracker - Location tracker	- (Sanfilippo, 2017) - (Roads, Mozer, & Busey, 2016)	-Point of view video -Contextual information - Highlight object of interest - Directed focus
Modelling the task with task analysis			
Approaches	Sensors used	Studies	Instructional Design Methods
Live telepresence: Expert provided audio instructions and visual guides during the live simulation	- Microphone - Video camera	- (Sanfilippo, 2017) - (Li, Lu, Chan, & Skitmore, 2015) - (Chia & Saakes, 2014) - (Datcu, Cidota, Lukosch, Oliveira, & Wolff, 2014) - (Chinthammit et al., 2014) - (Bordegoni et al., 2014)	- Point of view video, - Contextual information - Annotations - Haptic feedback - Cues and clues - Directed focus - Audio instructions
Modelling of the expert: Interviews with various experts		- (Schneider et al., 2017) - (Sebillo, Tortora, Vitiello, Paolino, & Ginige, 2015) - (Rozenblit et al., 2014) - (Meleiro, Rodrigues, Jacob, & Marques, 2014) - (Djajadiningrat, Lui, Chao, & Richard, 2016) - (Kim & Dey, 2016)	- Feedback - Contextual information, - Haptic feedback, - Interactive virtual objects
Assistance: Design of system to assist expert to train the apprentice		- (Daponte, De Vito, Riccio, & Sementa, 2014)	- Augmented mirror

Table 2
General Instructional Design Methods characteristics.

Description	
How can the features be described?	
What skills are being addressed?	
Requirements for Capture	**Requirements for Enactment**
What types of sensors are required?	What sensor is required for enactment?
What type of data must be captured?	What type of data is required enactment?
	How is this feature enabled by/for the apprentice?
	Which interaction means does the apprentice have?

2.4. Learning task

The IDMs in this component involve the apprentice in an active two-way interaction with the learning task itself. However, AR is usually used in the context of authentic learning, meaning that the learning task can be used either to support the authentic task or even to replace the authentic task in cases where the authentic task is not possible. Learning task IDMs are independent of supportive

Table 3
List of instructional design methods.

Instructional Design Methods	Description	Methods and means for capturing	Methods and means for enactment	Studies
Augmented Paths	● Augmenting virtual path overlaid on the physical world in a way which allows the apprentice to guide his/her motion with precision	● Recording of body movement ● Motion sensors ● Depth camera	● Visualizing expert paths using AR display ● Comparison to expert data ● Feedback by capturing apprentice movement with inertial sensor	● (Liu, Mei, Zhang, Lu, & Huang, 2017) ● (Stunt, Kerkhoffs, Horeman, van Dijk, & Tuijthof, 2016) ● (Sun et al., 2016) ● (Haug et al., 2014) ● (Rozenblit et al., 2014) ● (Tokuyasu et al., 2014) ● (Kritopoulou et al., 2016)
Augmented Mirror	● Augmented display where the apprentice can track his/her body, similar to dance rooms	● Recording of body movement ● Infrared sensor	● Large display where the apprentice can see himself/herself ● Infrared sensor to provide visual feedback	● (Chia & Saakes, 2014) ● (Meleiro et al., 2014) ● (Khan, 2015) ● (Daponte et al., 2014) ● (Lin et al., 2015) ● (Wei et al., 2014)
Highlight Object of Interest	● Highlights physical objects within the visual area, indicating to the trainee that the expert found that object of interest	● Recording of focus area ● Video recording ● Eye tracking sensor	● AR display to highlight objects ● Eye tracker for formative feedback	● (Roads et al., 2016) ● (Tong, Wang, Chen, & Chen, 2016) ● (Sand, Büttner, Paelke, & Röcker, 2016) ● (Rane, Kim, Marcano, & Gabbard, 2016)
Directed Focus	● Visual pointer for expert-determined relevant objects outside the visual area	● Recording of focus area ● Video recording ● Eye tracking sensor ● Location tracker	● AR display to show pointer ● Eye tracker for formative feedback ● Location tracker	● (Ke, Lee, & Xu, 2016) ● (Yarnall et al., 2014)
Point of View Video	● Provides unique trainee/expert point of view video which may not be available in a third person perspective	● Head-mounted camera ● Interaction mechanism to initiate and stop recording ● Zoom in to subject	● AR display for unobtrusive viewing of video ● Interaction and inference mechanism ● Zoom in to video	● (Milazzo, Farrow, & Fournier, 2016) ● (Chinthammit et al., 2014) ● (Bordegoni et al., 2014) ● (Sanfilippo, 2017)
Cues & Clues	● Cues and clues are pivots that trigger a solution search. They can be in the form of image or audio or any form of annotations. They should help the apprentice explore the solution with an annotation	● Record annotations ● Take a picture, save video, audio or text ● Use a physical object in the real world as an anchor for placing the cues and clues within the context ● Location tracker	● Display on demand ● Inference mechanism to automatically display the cues and clues ● Location tracker	● (Datcu et al., 2014) ● (Allain et al., 2015) ● Chang, Kang, Chang, & Liu, 2015)
Annotations	● Allow a physical object to be annotated by the expert during task demonstration (similar to sticky notes, but with more modes of information)	● Methods to tag media with a physical object ● Can be done with audio, video or text ● Location tracker	● AR display mechanism to read the annotations ● Mechanism for unobtrusive relay of information ● Location tracker	● (Datcu et al., 2014) ● (Bordegoni et al., 2014) ● (Li et al., 2015)
Object Enrichment	● Provides domain-related information about the physical artefact which is crucial to the performance of the task from an expert's point of view		● Object recognition camera ● Control over information displayed ● Display information on demand	● (Wang, Ong, & Nee, 2016) ● (Yarnall et al., 2014) ● (See, Billinghurst, Rengganaten, & Soo, 2016) ● (Perlini, Salinaro, Santalucia, & Musca, 2014)

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Table 3 (*continued*)

Instructional Design Methods	Description	Methods and means for capturing	Methods and means for enactment	Studies
Contextual Information	● Provides information about the process that is frequently changing but is important for performance	● Record of the steps involved in the process ● Recording of pivotal points that define the beginning and end of a task ● Tagging of dynamic information such as location of the colleague in collaborative tasks, for tracking	● Method to know when and where to provide the information ● Procedure information that depends on the context and is required for the task is presented when needed	● (Djajadiningrat et al., 2016) ● (Wang et al., 2016) ● (Sand et al., 2016) ● (Rane et al., 2016) ● (Yarnall et al., 2014) ● (Li et al., 2015) ● (Manuri, Sanna, Lamberti, Paravati, & Pezzolla, 2014) ● (Kersten-Oertel et al., 2016) ● (Kwon, Lee, Jeong, & Kim, 2014) ● (Islam, Kahol, Li, Smith, & Patel, 2016) ● (Sano, Sato, Shiraishi, & Otsuki, 2016) ● (Park, Kihl, Park, Kim & Chang, 2016) ● (Zhu, Ong, & Nee, 2014) ● (Mura, Dini, & Failli, 2016) ● (Sousa, Alves, & Rodrigues, 2016) ● (Kim & Dey, 2016) ● (Altimira et al., 2017) ● (Such, Ward, Hutabarat, & Tiwari, 2014) ● (Sebillo et al., 2015) ● (Borges, Martins, Naves, Bastos, & Lucena, 2016) ● (Perlini et al., 2014)
3D Models and Animation	● 3D models and animations assist in the easy interpretation of complex models and phenomena which require high spatial processing ability	● Allow expert to place 3D models and animations in physical space and time	● AR display to display the model and animation ● Interaction mechanism such as gestures to interact with the models where needed	● (De Ravé, Jiménez-Hornero, Ariza-Villaverde, & Taguas-Ruiz, 2016) ● (Radu, Doherty, DiQuollo, McCarthy, & Tiu, 2015) ● (Manuri et al., 2014) ● (Lee, Chen, & Chang, 2016) ● (Cirulis & Liepina, 2014) ● (Kamphuis, Barsom, Schijven, & Christoph, 2014)

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Table 3 (*continued*)

Instructional Design Methods	Description	Methods and means for capturing	Methods and means for enactment	Studies
Interactive Virtual Objects	● Manipulatable virtual objects to interface with physical interactions for practice. Unlike 3D models and animation, which render a phenomenon, these objects' behaviour outcomes are determined by the specific physical interaction		● Ontological models where behaviours of the model are defined by the relationships and variables ● Motion tracking with inertial sensors ● Haptic and visual feedback	● (De Paolis, Ricciardi, & Giuliani, 2014) ● (Liu et al., 2017) ● (Jang, Kim, Woo, & Wakefield, 2014) ● (Ke et al., 2016) ● (Radu et al., 2015) ● (Juanes, Gómez, Peguero, & Ruisoto, 2015) ● (Lok et al., 2014) ● (Gallegos-Nieto, Medellín-Castillo, González-Badillo, Lim, & Ritchie, 2016) ● (Lahanas, Loukas, Smailis, & Georgiou, 2015) ● (Lee et al., 2016) ● (Benedetti, Catenacci Volpi, Parisi, & Sartori, 2014) ● (Onishi, Mizushino, Noborio, & Koeda, 2014) ● (Freschi, Parrini, Dinelli, Ferrari, & Ferrari, 2015) ● (Oyekan et al., 2017) ● (Kowalewski et al., 2017)
Haptic Feedback	●Force feedback for perception and manipulation of authentic objects by means of a haptic sensor, to provide feedback and guidance	●Recording of hand movement ●Recording of body movement ●Defining of criteria for errorless operation ●Inertial sensors ●Infrared sensors	●Tracking the apprentice's motion with inertial sensor for comparison with expert performance ●Motors for providing haptic feedback	● (Stunt et al., 2016) ● (Haug et al., 2014) ● (Gallegos-Nieto et al., 2016) ● (Wang et al., 2016) ● (Sara et al., 2016) ●(Kim & Dey, 2016) ●(Asadipour et al., 2017) ●(Funk, Heusler, Akcay, Weiland, & Schmidt, 2016) ●(Ahmmad et al., 2014) ●(Araki et al., 2017)
X-ray Vision	● Visualizing the internal process invisible to the eye for enhanced understanding. Overlaying internal workings of the physical system on the physical object itself provides enhanced understanding of the system		● Visualization of the phenomena overlaid on the physical object ● Interaction mechanisms ● Object recognition	● (Kersten-Oertel et al., 2016) ● (Kwon et al., 2014) ● (Freschi et al., 2015) ● (Buń, Górski, Wichniarek, Kuczko, & Zawadzki, 2015) ● (Sara et al., 2016) ● (Cirulis & Liepina, 2014) ● (Islam et al., 2016) ● (Koreeda et al., 2016) ● Shekhar et al. (2010) ● (Kamphuis et al., 2014) ● (Chong et al., 2015) ● (Choi et al., 2017)

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Table 3 (*continued*)

Instructional Design Methods	Description	Methods and means for capturing	Methods and means for enactment	Studies
Formative Feedback	● Formative feedback is any feedback that can be provided by sensors and AR. It could be provided in visual, auditory or haptic form and should assist in conveying the procedural information	● Recording of any relevant sensor data in a meaningful manner such that it can be used for comparison with incoming data streams	● Measure of performance ● Mechanism to evaluate the overall performance	● (Matassa & Morreale, 2016) ● (Prabhu et al., 2017) ● (Horeman et al., 2015)
Summative Feedback	● Summative feedback is a versatile TM that is provided at the end of each practice session. It should allow reflection on the current performance	● Recording of any relevant sensor data in a meaningful manner such that it can be used for comparison of the final result of the expert and the apprentice	● Mechanism to assess the overall performance ● Measure of overall performance	● (Zhao et al., 2016)
Mobile Control	● Allows execution/visualization of remote action or controls which would otherwise require leaving the current workplace	● Task analysis to determine what actions and outputs are relevant ● Implementation to control devices remotely	● Implementation to control physical objects manually	
Ghost Track	● Allows visualization of the earlier recording of the apprentice himself/herself for reflection	● Sensors to capture necessary data for reflection ● Recording of the results of the action performed	● Visualization mechanisms ● Tracking of the current state of the apprentice	

Table 4
Instructional Design Methods classified based on the components of 4C/ID model and expert attributes.

IDMs	Performance Attributes			
	Motor skills	Cognitive skills	Collaborative skills	Perceptual skills
Learning task:				
Augmented mirror	✓	✓		
Augmented path	✓			
Interactive virtual objects	✓	✓	✓	
Mobile control				
Supportive information:				
Object enrichment		✓		✓
3D models & animation		✓		
X-ray vision	✓	✓	✓	✓
Cues & clues		✓		✓
Annotation		✓		✓
Contextual information	✓	✓	✓	✓
POV videos	✓	✓	✓	✓
Procedural information:				
Directed focus		✓		
Highlight objects		✓		✓
Haptic feedback	✓	✓		✓
Formative feedback	✓	✓		✓
Part-task practice:				
Ghost track	✓	✓		
Summative feedback		✓		

information and the procedural information. Table 4 lists the IDMs that support the learning task component. This component can be implemented with the IDMs in Table 4. For example, IDMs such as *augmented path* allow apprentices to imitate the expert performance for a smaller subset of the whole surgical complex skill.

2.5. Supportive information

IDMs in this component treat the apprentice as a non-dynamic receptor of supportive information that is not related to the procedure being executed. Supportive information is usually provided before the task execution, and during the task execution if needed. The "supportive information" section of Table 4 lists the IDMs that support this component by enabling the presentation of supportive information to the apprentice.

The supportive information component aims to elaborate the task model by establishing non-arbitrary relationships between the new elements and what apprentices already know. IDMs in this component, such as *object enrichment,* which enriches the physical object with virtual supportive information, allow apprentices to access domain-related information within the authentic context. This allows apprentices to link their existing mental model to its application during the training.

2.6. Just in time information

IDMs in this component treat the apprentice as a non-dynamic receptor of procedural information that is related to the procedure being executed. Table 4 lists the IDMs that have been identified in the "just in time" information component. AR has frequently been found to be well suited to providing procedural information in recurrent tasks, such as an assembly task. For example, an IDM such as *haptic feedback* is capable of providing corrective feedback precisely when needed.

2.7. Part-task practice

Only IDMs that contribute to the repetition of the recurrent task are added in this component. However, we could only identify *Summative feedback* as supporting this component. We have also listed *Ghost track* as an IDM that can support this component; this was not found in the literature, but was motivated by ghost records in games. This IDM can create ghost visualizations of a previous recording of an expert or the apprentice himself/herself, to provide a level at which the apprentice can aim in order to improve on the previous practice session.

To conclude, we have classified the IDMs that we identified based on the four components of 4C/ID, which provides us with an overview of how sensor-based AR can be used to create learning environments within the 4C/ID model. Such environments can improve the learning process between the expert and the apprentice, allowing the apprentice to learn better from the expert. Such systems also facilitate deliberate practice, which can potentially offer efficient support for the attainment of superior performance.

3. Discussion

Experts as mentors are crucial to the development of expertise in apprentices, but learning from experts has often proved to be a difficult task. Sensor-based AR introduces new possibilities for supporting apprentices and experts alike by capturing expert performance to train apprentices. Apprentices have the possibility to relive the expert's demonstration in a rich medium through additional sensor data augmented by AR. In addition, they can learn from the expert model at a more granular level, as experts may have overlooked details in their performance which could be crucial for the apprentice (Hinds, 1999). Capturing the expert performance and using it to train the apprentice helps address the shortage of experts to a certain degree, as an apprentice's performance can be compared with the expert model to provide formative feedback. Therefore, sensor-based AR posits potentials to simplify the process of learning from experts. To explore the use of sensors to capture expert performance and use sensor-based AR technology to train apprentices, we analysed 78 studies and identified 16 IDMs that use sensor-based AR for training apprentices based on expert data. The majority of IDMs are independent of the domain and applicable across domains. Furthermore, we classified the IDMs according to the components of the 4C/ID model to investigate whether sensor-based AR can support deliberate practice with the help of expert performance.

The exploration revealed that sensor-based AR has been used in various studies for training and supporting apprentices using experts as models. These methods varied from involving an expert in the system design and modelling an expert through various task analysis methods to using sensors to capture expert performance. In addition, we have also explored various types of expert performance attributes that can be captured with respective sensors. However, only 25 studies were identified that exclusively involved experts in their study. Seven approaches were identified from the 25 studies for capturing the expert performance. There is a need to emphasize more approaches to capture expert performance. Exploring new methods of capturing expert performance to allow apprentices to richly observe the expert demonstration could result in improved training efficiency. In addition, all the studies involved manual interpretation of recorded expert data between the capture and training phases. This increases the workload on the expert, which can result in hesitation to adopt the technology, as it is simply not feasible to edit the performance data manually for each learning task. To improve the learning process between the expert and the apprentice, a more automated approach needs to be developed which does not impose a significant additional workload on the expert.

It is worth mentioning that very few studies have exclusively claimed to address the cognitive process of the expert with the support of sensors. Cognitive aspects are not observable and cannot be directly captured by sensors. However, sensor data can be used to complement cognitive processes captured by performing a task analysis on the expert. For example, Jarodzka et al. (2013) used eye tracking data during the task analysis to explicate the cognitive process of the expert in order to understand the expert's action in classifying fish locomotion. Kim and Dey (2016a) explored different physiological sensors such as eye tracking, EEG sensors and heart rate, concluding that there is a strong possibility that these sensors can also be used to represent the cognitive process. Further studies are required to explore how sensor-based AR can address cognitive aspects of training and expertise development.

Our classification of IDMs (see Fig. 2) has revealed that the IDMs can be used for supporting deliberate practice within the 4C/ID model. We classified IDMs based on the four components of the 4C/ID model and on their intended pedagogic functionality. For example, haptic feedback was used to provide feedback on the procedures involved in performing the task (Wang et al., 2016), and thus was categorized under the procedural information component. Each component of the model consists of a list of IDMs which can be used to implement a sub-task in the 4C/ID model. In addition, we have also mapped the IDMs with the type of attribute each can

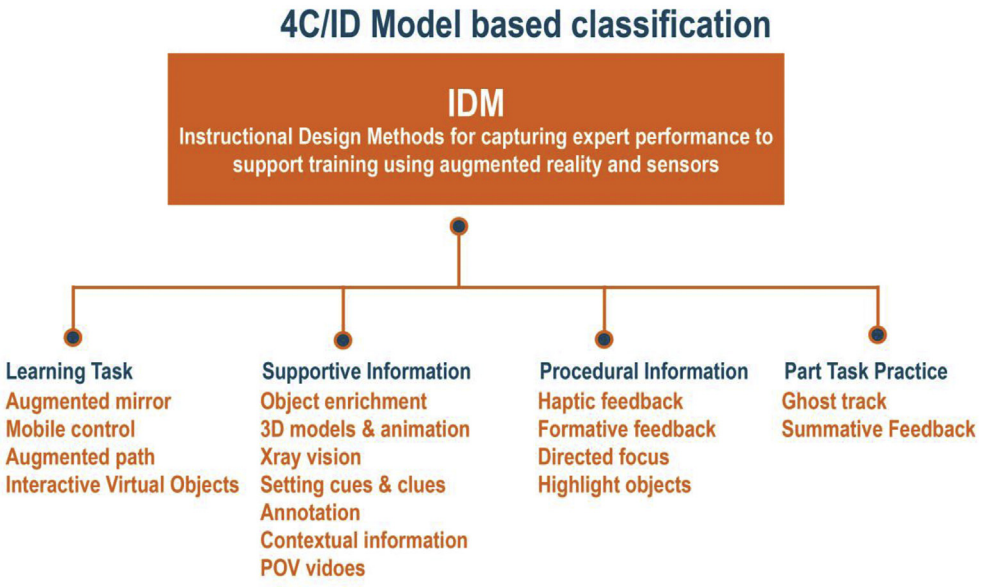


Fig. 2. 4C/ID model-based classification of IDMs.

Table 5
Steps for designing 4C/ID-based learning environments with IDMs.

No.	Step	Description
0	Pre-design:	It is crucial to perform task analysis of the task to be taught by involving an expert of the domain. Task analysis can be done using interviews or other methods.
1	Design learning task:	Break the complex task into a set of sub-tasks and determine the performance attributes for each sub-task. Determine the required supportive information and procedural information for the particular task. If the sub-task is a non-routine task, it is best to adopt authentic scenarios, as they are better learnt in this manner. The selection of IDMs should be based on the dominant attribute of the sub-task.
2	Sequence the task:	As a complex task usually consists of more than one sub-task, it should be ordered in progression of increasing difficulty. It should be projected into the learning plan that when the apprentice finishes the last task in the list he/she will have mastered the task.
3	Determine performance objectives:	Criteria for allowing the trainee to progress to the next sub-task should be outlined. This also helps in focusing the type of feedback that can be provided.
4	Design supportive information:	Information that helps the apprentice perform the non-recurrent aspects of the sub-task are determined at this stage. This step may involve information that the expert will not be able to create during the recording of expert performance.
5	Record expert performance:	Based on the sub-task and its attributes, proper sets of IDMs from the learning task category are selected. Each IDM consists of a set of recording requirements which should be met. The expert proceeds after wearing all the sensors and begins to demonstrate the sub-task. The sensor records all the information and generates the expert performance data, which supports the procedural task. It should be noted that, when recurrent tasks are practised, procedural information should be scaffolded.
6	Train in same/similar environment:	It is crucial that re-enactment of the learning task is done in the same or a very similar environment. Technical requirements aside, it also helps the apprentice in his/her learning of the task without any overhead load.
7	Follow through reflection:	The system can provide formative and summative feedback based on expert data, but it cannot replace the expert. Providing the expert with logged data of the apprentice's performance in a simple, readable format can facilitate the learning process between the expert and the apprentice.

be used to train. Performing task analysis on the complex task should yield one or more sub-tasks and the dominant attribute of the task. By selecting a proper set of IDMs that matches the attribute, a sensor-based AR training platform can be quickly designed.

While learning tasks in the 4C/ID model are arranged from lowest to highest difficulty to balance the task difficulty, the majority of studies do not address the affective aspects of tasks, which are crucial to deliberate practice. There are only a few exceptions, such as Altimira et al. (2017), who exclusively addressed affective aspects of the training by balancing difficulty in training to improve motivation. This could be an interesting area to look into for future studies; Bacca et al. (2014) have already emphasized the capability of AR to personalize training methods, reflecting the potential of sensor-based AR for affective aspects of the task. In addition, each study implemented and evaluated one or two IDMs together for their effectiveness in a concentrated application domain. When combining different IDMs, their effectiveness cannot be guaranteed, suggesting a need for further study of such a combination of IDMs. It should also be noted that most selected studies had a single domain of application, while we aim to improve the learning process between the expert and the apprentice regardless of their domain. Training tasks can often be very specific to the domain, while expertise is almost always specific to the domain of application. IDMs are abstract by definition, but designing a system following this approach may sometimes still require domain-specific implementations. To help facilitate this complex process, we have outlined a general operationalization guideline in Table 5 for designing 4C/ID-based learning environments.

4. Conclusion

This paper presents the review of 78 studies that implemented sensor-based AR technology that were developed for training skills, found in literature between 2014 and 2016. Our literature study might have excluded studies using specific sensors, such as eye trackers, due to the keyword “sensor” not being adopted in the eye tracking community and the expertise study community having yet to fully embrace modern technology. Nevertheless, the analysis performed revealed sensor-based AR technology as a promising solution to support the training of apprentices using expert performance data, which also has the potential to support deliberate practice within the 4C/ID approach. Moreover, we are addressing the issues identified in learning from experts in vocational training scenarios. First, we supplement captured expert performance data for the apprentice to observe in a rich, multimodal manner whereby he/she may be able to understand and identify knowledge bits which the expert may have overlooked. Second, we provide the possibility to use the expert performance data for training by means of other mechanisms such as feedback.

In this study, we focused on identifying state-of-the-art IDMs used by the prototypes in the selected studies. We did not analyse the IDMs identified according to their effectiveness or usability for training. Our main aim is to enhance the learning process between the expert and the apprentice. As such, we wanted to be independent of any domain-related results and implications. With young technology such as sensors and AR, which are only now beginning to mature, there is a need to explore ongoing research and the different creative outlets of the potentials that the technology can afford. Indeed, there is a need to evaluate the IDMs based on their effectiveness. However, rather than studying the effectiveness of the IDMs, we intended to see if the sensor-based AR can enhance the expert-apprentice learning process independently of the domain, and whether it can eventually support deliberate practice in apprentices.

The identified IDMs are promising and show high potential for effective implementation, as the sensor and AR technology will

continue to improve in future. Research gaps such as the use of sensors to capture cognitive and affective aspects of expert performance provide an interesting area of study. While there are still many bottlenecks to be dealt with before the full potential of sensor-based AR technology can be realized, this literature review contributes an overview of the state of the art in instructional methods for using AR and sensor technology with expert performance. The study also touched on the potential of sensor-based AR for supporting deliberate practice. For our future research, we would like to use the identified IDMs to build new prototypes that embrace the 4C/ID model. The research group is currently developing generic capturing and AR learning components to be used in summative studies for the effectiveness, efficiency and usability of the IDMs.

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Appendix A

List of analysed studies and their implemented transfer mechanism

Studies	Description	Sensor Used	Experts Involvement	Instructional Methods
(De Paolis et al., 2014)	Serious Game for assessment of skill in laparoscopic suture training by physical modelling of virtual environments. Gamification of surgical skill performed on virtual models using the haptic sensors for physical haptic feedback	Haptic sensors	–	Interactive virtual object
(Liu et al., 2017)	AR system for hand movement rehabilitation. Patients were asked to imitate a trajectory or move virtual objects	Optical marker trackers	–	Augmented paths Interactive virtual objects
(Stunt et al., 2016)	Prototype passport v2 was used to train minimally invasive surgery by providing natural sensory feedback. Participants were also asked to perform a guided navigation motion	Depth camera and haptic band	–	Augmented paths Haptic feedback
(Sun et al., 2016)	Motion detection system to assess hand dexterity for surgical knot tying	Leap motion	Recorded expert hand movement path to use as comparison for assessment	Augmented paths Feedback
(Hahn, Ludwig, & Wolff, 2015)	Support and training for assembly of printed board circuit by highlighting component retrieval location	Smart glass and QR code tracking camera	–	Directed focus Highlight object of interest
(Haug et al., 2014)	Analysis of laparoscopic surgical skills by capturing motion and translation in 3D space with the aim of classifying calculated features of the performance	Wireless inertial sensor and surgical tools with inertial tracker	Recorded the expert hand movement and the movement of the surgical tools including their translation	Augmented path
(Rozenblit et al., 2014)	Prototype for providing cognitive and haptic feedback for guided surgical training using computer-modelled expert attributes	Embedded sensors in the surgical instruments	Models the judgement criteria used by experienced surgeons and provides scalability characteristics in three key aspects: integration of new expert opinions; integration of new evaluation metrics; and integration of new performance data, for the constant improvement of an objective scoring system	Augmented path Haptic feedback
(Tokuyasu et al., 2014)	Training of endoscopic surgery skills. The apprentice was asked to use a	Optical tracker	–	Augmented path

	surgical tool to track a Japanese letter displayed through smart glass			
(De Ravé et al., 2016)	Prototype for teaching descriptive geometry learning with spatial 3D visualizations of the complex model in a series of step-by-step exercises	Augmented reality display	–	3D models and animation
(Chia & Saakes, 2014)	Training fine motor skills and hand eye coordination by imitating the expert's chopstick movements. overlaid using smart glasses	Potentiometer for force and accelerometer for motion	Recorded expert hand movements along with chopsticks to be overlaid	Augmented mirror
(Meleiro et al., 2014)	Assisting children with motor impairments for walking with a therapy for a sequence of poses	Kinect for posture	Interview to understand the therapy	Augmented mirror
(Khan, 2015)	Prototype for capturing expert performing traditional Arab dance to create a teaching system	Kinect	Recording expert demonstration	Augmented mirror
(Daponte et al., 2014)	Prototype for calculation of range of motion for elbow joint for rehabilitation programme which was stored and forwarded to the expert	Kinect	Support system for the expert to design therapies	Augmented mirror
(Lin et al., 2015)	Prototype to investigate the effects of game elements intervention on the jumping performance of children	Kinect	–	Augmented mirror
(Wei et al., 2014)	Designed to evaluate and monitor dance performance using the expert performance as a benchmark	Use of accelerometer for motion and rhythm	Captured the expert performance	Augmented mirror
(Jang et al., 2014)	Training platform for sculpting on a virtual model with physical hand and finger movements	Depth sensing camera	Interview of the experts to determine the performance criteria	Interactive virtual object
(Ke et al., 2016)	Prototype for teaching training and classroom management in a mixed reality environment with non-player characters designed to intervene as students	Kinect Eye tracking Smart glasses	–	Directed focus Interactive virtual object
(Radu et al., 2015)	Teaching geometry with a game that required children to build a bridge across the river for the game character to cross. Physical blocks were also provided to support spatial experimentation	Tablet camera	–	Interactive virtual objects 3D models and animation
(Juanes et al., 2014)	Simple prototype that allowed the learner to practise laparoscopic surgery by using gestures to interact with the virtual object	Leap motion	–	Interactive virtual object
(Kritopoulou et al., 2016)	Prototype for teaching pottery-making using augmented feedforward and feedback to train sensorimotor skills	Depth camera like leap motion Projector	Expert operational model which encapsulated all the information of the gesture obtained from the expert. Therefore, the model includes the subtle details of the quality of the gesture, which can distinguish an Expert from a Learner	Augmented path Feedback
(Lok et al., 2014)	Team training simulation with non-player characters for training collaboration in medical situations	Kinect and microphone	–	Interactive virtual objects
(Roads et al., 2016)	Prototype to train fingerprint-matching skill by highlighting relevant areas and using fixation to assess the performance	Eye tracking	Use of expert model to the novice model	Highlight objects of Interest
		Video camera	–	

(Milazzo et al., 2016)	Participants were semi-professional players who were required to watch the video of a player making decisions in game			Point of view video
(Djajadiningrat, 2016)	Low-cost Augmented Reality simulator for sudden cardiac arrest emergency training by following a sequence of instructions in video format and the contextual information provided in the proximity of a physical mannequin	Optical tracker	Expert interviewed during design of instructions	Contextual information
(Gallegos-Nieto et al., 2016)	Designed for the evaluation of the influence of haptic-enabled virtual assembly training. Learners could use a haptic device to assemble virtual components	Haptic motor device	–	Haptic feedback Interactive virtual objects
(Datcu et al., 2014)	Designed for collaboration for in-flight maintenance allowing expert to assist from a different location. The expert was provided with the point of view video of the trainee with contextual icons such as arrows that were displayed to the trainee	Head mounted camera	Telepresence	Annotations Cues and clues
(Lahanas et al., 2015)	Prototype for assessment of minimally invasive surgery skills using a box trainer equipped with a camera and laparoscopic tools with built-in motion sensors that allowed the learner to manipulate objects in a virtual environment	Camera, accelerometer built into the surgical tools	–	Interactive virtual objects
(Chen et al., 2015)	Surgical navigation system for sacroiliac joint screw insertion on a mannequin which synchronized with the 3D model being manipulated by the trainee during practice on the mannequin	Motion tracker	–	Interactive virtual objects
(Wang et al., 2016)	Multimodal assembly guidance system that provided procedural information and haptic feedback on error detection	Haptic band Leap motion	–	Object enrichment Contextual information Haptic feedback
(Benedetti et al., 2014)	Prototype for attention training on adult suffering from a frontal syndrome using a brain computer interface that moved the 3D object with brain waves	EEG	–	Interactive virtual objects
(Onishi et al., 2014)	Dental surgery training prototype that allowed learners to practise on a virtual 3D model of teeth. The prototype also provided haptic feedback	Magnetic motion sensor Haptic device camera	–	Interactive virtual objects
(Tong et al., 2016)	Hovering hand pointer assisted the trainee by pointing at the area that needed to be addressed during the assembly of the motherboard	Camera designed to recognize the motherboard	–	Highlight object of interest
(Sand et al., 2016)	Assembly assistance of Lego with projection-based AR which displayed instructions and highlighted the box containing the next piece. Foot pedals were used to shift to the next step	Camera and projector	–	Contextual information Highlight object of interest

(Rane et al., 2016)	Prototype for training drivers' situational awareness and perception by providing driving aids on location and contextual information	–	–	Contextual information Highlight object of interest
(Yarnall et al., 2014)	AR mentoring system for maintenance	Head mounted camera Microphone	Expert model that tracks its orientation to the object being repaired to provide feedback on the correct placement	Contextual information Directed focus Object enrichment Feedback
(Chinthammit et al., 2014)	Motor rehabilitation system using visual augmentation to allow the therapist and the patient to inhabit each other's viewpoint	Head mounted camera	Telepresence of expert. The patient had to imitate the therapist's hand which was overlaid on the patient's vision	Augmented path Point of view video
(Bordegoni et al., 2014)	Prototype to support collaboration between an expert and a novice in a maintenance task by sharing the novice's point of view video and allowing the expert to interact with the video in the form of annotations which were displayed on the novice's glasses	Head mounted camera	Telepresence. Possibility for the expert to put annotations in the novice's field of view	Annotations Cues and clues Point of view
(Li et al., 2015)	Training system for safe precast installation in construction by improving collaboration	Motion tracking with optical camera	Telepresence. The novice's position was tracked and displayed on the screen where the expert could annotate areas of interest for the novice	Annotations Contextual information
(Sanfilippo, 2017)	Designed to train situational awareness in Maritime training by providing live guidance by the expert who provided guidance to the areas of interest	Eye tracker Oculus rift	Experts shared the simulation view and directed the trainee to act accordingly	Point of view video Audio instructions
(See et al., 2016)	Enhanced heart murmurs to train residents in recognizing them	Mobile phone and electronic stethoscope	–	Object enrichment
(Manuri et al., 2014)	AR-based maintenance support system that provided the procedural information and 3D models of the objects	–	–	3D models and animation Contextual information
(Kersten-Oertel et al., 2016)	System designed to support the planning of brain tumour surgery by overlaying personalized and real-time updated brain tumour data on the patient himself/herself	Infrared tracking Optical tracking	–	Contextual information X-ray vision
(Lee et al., 2016)	3D hologram-based prototype for training mental rotation in older adults	Leap motions	–	3D models and animation
(Kwon et al., 2014)	For training basic life support without an instructor. Consisted of simulated realistic scenario with visual and auditory feedback	Interactive mannequin and projector	–	X-ray vision Contextual information
(Freschi et al., 2015)	Prototype for training ultrasound imaging by improving hand-eye co-ordination and 3D depth perception	Ultrasound 6 DOF electromagnetic sensor	–	Interactive virtual objects X-ray vision with overlaid ultrasound reading

(Buń et al., 2015)	Simulation of ultrasound imaging with a mannequin focusing on orientation of the ultrasound device and tracking the path of the motion	Ultrasound Motion sensor	–	X-ray vision
(Sara et al., 2016)	Provided tactile feedback for arteries using a wearable pressure-sensitive glove. Hints and related information were also provided	Potentiometer	–	Haptic feedback X-ray vision
(Cirulis & Liepina, 2014)	Interactive augmented 3D environment that provided passive tactile feedback for teaching veterinary anatomy skills by overlaying 3D augmentations on a physical model	–	–	3D models X-ray vision
(Islam et al., 2016)	Video-based skill assessment of minimally invasive surgical skills by measuring hand-eye coordination and depth perception. It also provided real-time feedback and the score	Depth sensor camera	–	X-ray vision Contextual information
(Koreeda et al., 2016)	Supporting system to allow the surgeons to visualize obscured regions in real time	2 endoscopic cameras	–	X-ray vision
(Shekhar et al., 2010)	A stereoscopic vision system for visualizing surgical anatomy with true depth for training spatial perception	Ultrasound scanner and optical trackers	–	X-ray vision
(Kamphuis et al., 2014)	Displayed internal organs in a real-time tracked body for anatomy education	Kinect	–	X-ray vision 3D model and animation
(Western, Hristov, & Schlosser, 2015)	System for ultrasound guided radiation therapy for precise penetration of the radiation to aim at the correct tissue	Ultrasound	–	X-ray vision
(Chong et al., 2015)	Training environment for manual ultrasonic testing using real-time visualization of ultrasound data	Ultrasound	–	X-ray vision
(Allain et al., 2015)	Navigation system for visually-impaired children based on a game which required them to find the path using auditory cues	Oculus rift	–	Cues and clues
(Chang et al., 2015)	Prototype for training the correct reactions in patients with cognitive impairments. The patients were provided with visual and auditory cues to support them to make the correct decision	Optical tracker	–	Cues and clues
(Sano et al., 2016)	System for supporting novice players to plan their actions to reduce the skill gap by visualizing the ball trajectory in a collaborative soccer game	22 motion cameras and projectors to project the path of the ball	–	Contextual information
(Park et al., 2016)	A serious game platform to help children with ADHD using a dynamically adaptive intervention scheme where the character is controlled by brain-computer interface	EEG Kinect	–	Feedback Contextual information
(Zhu et al., 2014)	A maintenance support system that provided instructions and information	Optical tracking camera	–	Contextual information

	about the equipment according to the expertise level of the user			
(Mura et al., 2016)	Support system for manual assembly workers which superimposed the correct assembly sequence and provided feedback based on data from a pressure sensor placed under the box containing each part	Potentiometer	–	Contextual information Feedback
(Sousa et al., 2016)	System to assist novice pool players using AR by projecting the shot path calculated based on the cue orientation of the player	Kinect projector	–	Contextual information
(Kim & Dey, 2016)	Prototype with the concept of augmenting drivers' senses to represent information in a way that minimized perceptual and cognitive load processing	Eye tracking EEG, heart rate sensor	Task analysis with expert to identify relevant aspects of the task	Haptic feedback Contextual information
(Choi et al., 2017)	Surgical navigation system for bone tumour resection by augmenting the path of the laser beam	Ultrasound	–	X-ray vision
(Oyekan et al., 2017)	Remote collaboration platform with digitized human and workpiece for interactions allowing remote communication and interaction with the environment	Kinect	–	Interactive virtual objects annotation
(Altimira et al., 2017)	Platform for enhancing table tennis player motivation by balancing gameplay digitally using a projector to highlight areas of the table where the expert may play, limiting his/her performance	Projector	–	Contextual information
(Such et al., 2014)	Prototype for training composite layup by guiding the trainee with instructions and feedback based on his/her hand movement	Kinect	–	Contextual information
(Sebillo et al., 2015)	Designed for training for collaboration in emergency situations, providing relevant information such as status of others and location data	GPS	The experts designed the simulation	Contextual information
(Borges et al., 2016)	Multimodal training system for electric-powered wheelchair users with brain-computer interface	EEG	–	Contextual information
(Perlini et al., 2014)	Guided cardiac auscultation training on a mannequin to assist residents to identify different cardiac diagnoses by listening to the heart murmurs	–	–	Contextual information Object enrichment
(Asadipour et al., 2017)	Provided multimodal visualization to assist in palpation task. Also used gamification to improve skill acquisition	Potentiometer	Captured expert pressure application	Haptic feedback
(Matassa & Morreale, 2016)	Supporting singers with tactile and visual feedback on their performance in real time	Heart Rate sensor Vibration collector	–	Feedback
(Funk et al., 2016)	Providing haptic auditory or visual feedback on Lego assembly task to measure the effectiveness of each type of feedback	Kinect	–	Haptic feedback
(Zhao et al., 2016)	Designed for the assessment of thumb release in archery and provided summative feedback on performance	Accelerometer infused in glove	Captured 50 samples from experts to use as a benchmark for the assessment	Feedback

(Ahmmad et al., 2014)	Designed to measure the psychomotor skills and dexterity of the novice for surgical procedures using a haptic-enabled surgical device	Haptic device	Captured expert performance on psychomotor skills	Haptic feedback
(Araki et al., 2016)	Prototype to assess the gripping and reaction force of the novice during laparoscopic surgery. The experiment was performed on a pig carcass	Pressure-sensitive forceps Accelerometer	Recorded amount of pressure used by experts during the procedure	Haptic feedback
(Prabhu et al., 2017)	Training platform for composite layup task, providing feedback based on decoded key steps of the captured performance	Kinect	Captured expert performance and manually decoded the recording into individual steps	Feedback
(Horeman et al., 2014)	Provided visual feedback on the force applied on a knot-tying surgical procedure with different coloured lights indicating different levels	Potentiometer	–	Feedback
(Kowalewski et al., 2016)	Laparoscopic surgery training prototype based on an expert model which provided real-time feedback on the performance of the trainee in a simulated environment	Kinect NDI polaris camera 2 infrared cameras	Data collected from four experts' demonstration	Interactive virtual objects Feedback

References

Ahmmad, S. N. Z., Ming, E. S. L., Fai, Y. C., & Narayanan, A. L. T. (2014). Experimental study of Surgeon's psychomotor skill using sensor-based measurement. *Procedia Computer Science, 42*, 130–137. https://doi.org/https://doi.org/10.1016/j.procs.2014.11.043.

Allain, K., Dado, B., Gelderen, M. Van, Hokke, O., Oliveira, M., Bidarra, R., et al. (2015). An audio game for training navigation skills of blind children. *2015 IEEE 2nd VR workshop on sonic interactions for virtual environments, SIVE 2015 - proceedings* (pp. 49–52). . https://doi.org/10.1109/SIVE.2015.7361292.

Altimira, D., Mueller, F. Floyd, Clarke, J., Lee, G., Billinghurst, M., et al. (2017). Enhancing player engagement through game balancing in digitally augmented physical games. *International Journal of Human-Computer Studies, 103*, 35–47. https://doi.org/10.1016/J.IJHCS.2017.02.004.

AR/VR funding in 2016 already 85% Growth on 2015. Retrieved March 18, 2018, from https://www.cbinsights.com/research/augmented-virtual-reality-funding-trends-q2-2016/.

Araki, A., Makiyama, K., Yamanaka, H., Ueno, D., Osaka, K., Nagasaka, M., et al. (2016). Comparison of the performance of experienced and novice surgeons: Measurement of gripping force during laparoscopic surgery performed on pigs using forceps with pressure sensors. *Surgical Endoscopy, 31*(4), 1999–2005. https://doi.org/10.1007/s00464-016-5153-x.

Araki, A., Makiyama, K., Yamanaka, H., Ueno, D., Osaka, K., Nagasaka, M., et al. (2017). Comparison of the performance of experienced and novice surgeons: Measurement of gripping force during laparoscopic surgery performed on pigs using forceps with pressure sensors. *Surgical Endoscopy, 31*(4), 1999–2005. https://doi.org/10.1007/s00464-016-5153-x.

Asadipour, A., Debattista, K., & Chalmers, A. (2017). Visuohaptic augmented feedback for enhancing motor skills acquisition. *The Visual Computer, 33*(4), 401–411. https://doi.org/10.1007/s00371-016-1275-3.

Bacca, J., Baldiris, S., Fabregat, R., Graf, S., & Kinshuk (2014). Augmented reality trends in education: A systematic review of research and applications. *Educational Technology & Society, 17*(4), 133–149.

Benedetti, F., Catenacci Volpi, N., Parisi, L., & Sartori, G. (2014). *Attention training with an easy-to-use brain computer interface. Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*, *Vol. 8526*, Cham: Springer236–247. LNCS https://doi.org/10.1007/978-3-319-07464-1_22.

Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher, 13*(6), 4–16. https://doi.org/10.3102/0013189X013006004.

Bloom, B. S., & Sosniak, L. A. (1985). *Developing talent in young people.* New York, NY: Ballantine Books.

Bordegoni, M., Ferrise, F., Carrabba, E., Donato, M., Di, Fiorentino, M., & Uva, A. E. (2014). An application based on augmented reality and mobile technology to support remote maintenance. In J. Perret,, V. Basso,, F. Ferrise,, K. Helin,, V. Lepetit,, & J. Ritchie, (Eds.). *EuroVR 2014 - conference and exhibition of the european association of virtual and augmented reality*The Eurographics Associationhttps://doi.org/10.2312/eurovr.20141351.

Borges, L. R., Martins, F. R., Naves, E. L. M., Bastos, T. F., & Lucena, V. F. (2016). Multimodal system for training at distance in a virtual or augmented reality environment for users of electric-powered wheelchairs. *IFAC-PapersOnLine, 49*(30), 156–160. https://doi.org/10.1016/J.IFACOL.2016.11.146.

Bower, M., & Sturman, D. (2015). What are the educational affordances of wearable technologies? *Computers & Education, 88*, 343–353. https://doi.org/https://doi.org/10.1016/j.compedu.2015.07.013.

Buń, P., Górski, F., Wichniarek, R., Kuczko, W., & Zawadzki, P. (2015). Immersive educational simulation of medical ultrasound examination. *Procedia Computer Science, 75*, 186–194. https://doi.org/https://doi.org/10.1016/j.procs.2015.12.237.

Carey, B. (2014). *How do you get to carnegie Hall?* Talent - The New York Times. Retrieved March 18, 2018, from https://mobile.nytimes.com/2014/07/15/science/which-matters-more-talent-or-practice.html?referrer=.

Chang, Y.-J., Kang, Y.-S., Chang, Y.-S., & Liu, H.-H. (2015). ARCoach 2.0: Optimizing a vocational prompting system based on augmented reality for people with cognitive impairments. *Proceedings of the 17th international ACM SIGACCESS conference on computers & accessibility*New York, NY, USA: ACMhttps://doi.org/10.1145/2700648.2811354.

Chen, X., Xu, L., Wang, Y., Wang, H., Wang, F., Zeng, X., et al. (2015). Development of a surgical navigation system based on augmented reality using an optical see-through head-mounted display. *Journal of Biomedical Informatics, 55*, 124–131. https://doi.org/10.1016/j.jbi.2015.04.003.

Chia, F.-Y., & Saakes, D. (2014). *Interactive training chopsticks to improve fine motor skills. Proceedings of the 11th conference on advances in computer entertainment technology*New York, NY, USA: ACM57:1–57:4. https://doi.org/10.1145/2663806.2663816.

Chinthammit, W., Merritt, T., Pedersen, S., Williams, A., Visentin, D., Rowe, R., et al. (2014). Ghostman: Augmented reality application for telerehabilitation and remote instruction of a novel motor skill. *BioMed Research International,* 646347. 2014 https://doi.org/10.1155/2014/646347.

Choi, H., Park, Y., Lee, S., Ha, H., Kim, S., Cho, H. S., et al. (2017). A portable surgical navigation device to display resection planes for bone tumor surgery. *Minimally*

Invasive Therapy & Allied Technologies, 1–10. https://doi.org/10.1080/13645706.2016.1274766.
Chong, Y. B., Bennecer, A., Hagglund, F., Siddiqi, S., Kappatos, V., Selcuk, C., et al. (2015). A new synthetic training environment system based on an ICT-approach for manual ultrasonic testing. *Measurement, 71*, 11–22. https://doi.org/10.1016/J.MEASUREMENT.2015.04.013.
Cirulis, A., & Liepina, E. (2014). *Designing an interactive and augmented 3d environment with passive tactile feedback for veterinary training. Lecture notes in computer science, Vol. 8853,* 442–449. https://doi.org/10.1007/978-3-319-13969-2_35.
Collins, A., Brown, J. S., & Holum, A. (1991). Cognitive apprenticeship: Making thinking visible. *American Educator, 6*(11), 38–46.
Daponte, P., De Vito, L., Riccio, M., & Sementa, C. (2014). Design and validation of a motion-tracking system for ROM measurements in home rehabilitation. *Measurement. Journal of the International Measurement Confederation, 55*, 82–96. https://doi.org/10.1016/j.measurement.2014.04.021.
Datcu, D., Cidota, M., Lukosch, S., Oliveira, D. M., & Wolff, M. (2014). Virtual Co-location to support remote assistance for inflight maintenance in ground training for space missions. *Proceedings of the 15th international conference on computer systems and technologies* (pp. 134–141). New York, NY, USA: ACM. https://doi.org/10.1145/2659532.2659647.
De Corte, E., for Research on Learning, E. A., Instruction, Verschaffel, L., Van Merriënboer, J., & Entwistle, N. (2003). *Powerful learning environments: Unravelling basic components and dimensions.* Pergamon.
De Paolis, L. T., Ricciardi, F., & Giuliani, F. (2014). Development of a serious game for laparoscopic suture training. In L. T. De Paolis, & A. Mongelli (Eds.). *Augmented and virtual reality* (pp. 90–102). Cham: Springer International Publishing.
De Ravé, E. G., Jiménez-Hornero, F. J., Ariza-Villaverde, A. B., & Taguas-Ruiz, J. (2016). DiedricAR: A mobile augmented reality system designed for the ubiquitous descriptive geometry learning. *Multimedia Tools and Applications, 75*(16), 9641–9663. https://doi.org/10.1007/s11042-016-3384-4.
Definition of sensors in English by Oxford Dictionaries. Retrieved March 16, 2018, from https://en.oxforddictionaries.com/definition/sensor.
Djajadiningrat, T. (2016). Virtual Trainer : A low cost AR simulation of a sudden cardiac arrest emergency. *Proceedings of the 2016 ACM conference on designing interactive systems* (pp. 607–618). . https://doi.org/10.1145/2901790.2901914.
Djajadiningrat, T., Lui, P., Chao, P.-Y., & Richard, C. (2016). Virtual trainer: A low cost AR simulation of a sudden cardiac arrest emergency. *Proceedings of the 2016 ACM conference on designing interactive systems* (pp. 607–618). New York, NY, USA: ACM. https://doi.org/10.1145/2901790.2901914.
Ericsson, K. A., Charness, N., Feltovich, P. J., & Hoffman, R. R. (2006). *The Cambridge handbook of expertise and expert performance. Cambridge Handbooks in Psychology.* Cambridge University Press.
Ericsson, K. A., Prietula, M. J., & Cokely, E. T. (2007). The making of an expert. *Harvard Business Review, 85*(7–8), 114–121. https://doi.org/Article.
Freschi, C., Parrini, S., Dinelli, N., Ferrari, M., & Ferrari, V. (2015). Hybrid simulation using mixed reality for interventional ultrasound imaging training. *International Journal of Computer Assisted Radiology and Surgery, 10*(7), 1109–1115. https://doi.org/10.1007/s11548-014-1113-x.
Funk, M., Heusler, J., Akcay, E., Weiland, K., & Schmidt, A. (2016). Haptic, auditory, or visual?: towards optimal error feedback at manual assembly workplaces. *Proceedings of the 9th ACM international conference on pervasive technologies related to assistive environments* (pp. 43:1–43:6). New York, NY, USA: ACM. https://doi.org/10.1145/2910674.2910683.
Gallegos-Nieto, E., Medellín-Castillo, H. I., González-Badillo, G., Lim, T., & Ritchie, J. (2016). The analysis and evaluation of the influence of haptic-enabled virtual assembly training on real assembly performance. *International Journal of Advanced Manufacturing Technology, 89*(1–4), 1–18. https://doi.org/10.1007/s00170-016-9120-4.
Guest, W., Wild, F., Vovk, A., Fominykh, M., Limbu, B., Klemke, R., et al. (2017). *Affordances for capturing and re-enacting expert performance with wearables. Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics), Vol. 10474*LNCShttps://doi.org/10.1007/978-3-319-66610-5_34.
Hahn, J., Ludwig, B., & Wolff, C. (2015). Augmented reality-based training of the PCB assembly process. *Proceedings of the 14th international conference on mobile and ubiquitous multimedia* (pp. 395–399). . https://doi.org/10.1145/2836041.2841215.
Haug, T., Rozenblit, J. W., & Buchenrieder, K. (2014). *Movement analysis in laparoscopic surgery trainingSimulation series* (46th ed.). The Society for Modeling and Simulation International292–299.
Hinds, P. (1999). The curse of expertise: The effects of expertise and debiasing methods on prediction of novice performance. *Journal of Experimental Psychology: Applied, 5*(2), 205–221. https://doi.org/10.1037/1076-898X.5.2.205.
Hinds, P. J., Patterson, M., & Pfeffer, J. (2001). Bothered by abstraction: The effect of expertise on knowledge transfer and subsequent novice performance. *Journal of Applied Psychology, 86*(6), 1232–1243. https://doi.org/10.1037/0021-9010.86.6.1232.
Horeman, T., Blikkendaal, M. D., Feng, D., Van Dijke, A., Jansen, F., Dankelman, J., et al. (2014). Visual force feedback improves knot-tying security. *Journal of Surgical Education, 71*(1), 133–141. https://doi.org/10.1016/j.jsurg.2013.06.021.
Horeman, T., Sun, S., Tuijthof, G. J. M., Jansen, F. W., Meijerink, J. W. J. H. J., & Dankelman, J. (2015). Design of a box trainer for objective assessment of technical skills in single-port surgery. *Journal of Surgical Education, 72*(4), 606–617. https://doi.org/10.1016/j.jsurg.2015.02.002.
Islam, G., Kahol, K., Li, B., Smith, M., & Patel, V. L. (2016). Affordable, web-based surgical skill training and evaluation tool. *Journal of Biomedical Informatics, 59*, 102–114. https://doi.org/10.1016/j.jbi.2015.11.002.
Jang, S. A., Kim, H. I., Woo, W., & Wakefield, G. (2014). *AiRSculpt: A wearable augmented reality 3D sculpting system. Distributed, ambient, and pervasive interactions. DAPI 2014. Lecture notes in computer science, Vol. 8530*, 130–141. https://doi.org/10.1007/978-3-319-07788-8_13.
Jarodzka, H., Van Gog, T., Dorr, M., Scheiter, K., & Gerjets, P. (2013). Learning to see: Guiding students' attention via a Model's eye movements fosters learning. *Learning and Instruction, 25*, 62–70. https://doi.org/10.1016/j.learninstruc.2012.11.004.
Juanes, J. A., Gómez, J. J., Peguero, P. D., & Ruisoto, P. (2015). Practical applications of movement control technology in the acquisition of clinical skills. *Proceedings of the 3rd international conference on technological ecosystems for enhancing multiculturality* (pp. 13–17). New York, NY, USA: ACM. https://doi.org/10.1145/2808580.2808583.
Juanes, J. A., Hernández, D., Ruisoto, P., García, E., Villarrubia, G., & Prats, A. (2014). Augmented reality techniques, using mobile devices for learning human anatomy. *Proceedings of the second international conference on technological ecosystems for enhancing multiculturality* (pp. 7–11). . https://doi.org/10.1145/2669711.2669870.
Kamphuis, C., Barsom, E., Schijven, M., & Christoph, N. (2014). Augmented reality in medical education? *Perspectives on Medical Education, 3*(4), 300–311. https://doi.org/10.1007/s40037-013-0107-7.
Ke, F., Lee, S., & Xu, X. (2016). Teaching training in a mixed-reality integrated learning environment. *Computers in Human Behavior, 62*, 212–220. https://doi.org/https://doi.org/10.1016/j.chb.2016.03.094.
Kersten-Oertel, M., Gerard, I. J., Drouin, S., Petrecca, K., Hall, J. A., & Louis Collins, D. (2016). Towards augmented reality guided craniotomy planning in tumour resections. In G. Zheng, H. Liao, P. Jannin, P. Cattin, & S.-L. Lee (Eds.). *Medical imaging and augmented reality* (pp. 163–174). Cham: Springer International Publishing.
Khan, M. (2015). Transmitting Al ardha: Traditional arab sword dance. *International Journal of Heritage in the Digital Era, 4*(1), 71–85. https://doi.org/10.1260/2047-4970.4.1.71.
Kim, S., & Dey, A. K. (2016a). Augmenting human senses to improve the user experience in cars: Applying augmented reality and haptics approaches to reduce cognitive distances. *Multimedia Tools and Applications, 75*(16), 9587–9607. https://doi.org/10.1007/s11042-015-2712-4.
Kirschner, P., & van Merriënboer, J. J. G. (2008). *21st century education: A reference handbook.* Thousand Oaks: SAGE Publications, Inc. https://doi.org/10.4135/9781412964012NV-2.
Koreeda, Y., Kobayashi, Y., Ieiri, S., Nishio, Y., Kawamura, K., Obata, S., et al. (2016). Virtually transparent surgical instruments in endoscopic surgery with augmentation of obscured regions. *International Journal of Computer Assisted Radiology and Surgery, 11*(10), 1927–1936. https://doi.org/10.1007/s11548-016-1384-5.
Kowalewski, K. F., Hendrie, J. D., Schmidt, M. W., Garrow, C. R., Bruckner, T., Proctor, T., et al. (2016). Development and validation of a sensor- and expert model-based training system for laparoscopic surgery: The iSurgeon. *Surgical Endoscopy, 31*(5), 2155–2165. https://doi.org/10.1007/s00464-016-5213-2.
Kowalewski, K. F., Hendrie, J. D., Schmidt, M. W., Garrow, C. R., Bruckner, T., Proctor, T., et al. (2017). Development and validation of a sensor- and expert model-based training system for laparoscopic surgery: The iSurgeon. *Surgical Endoscopy and Other Interventional Techniques, 31*(5), 2155–2165. https://doi.org/10.1007/

s00464-016-5213-2.
Kritopoulou, P., Manitsaris, S., & Moutarde, F. (2016). Towards the design of augmented feedforward and feedback for sensorimotor learning of motor skills. *Proceedings of the 3rd international symposium on movement and computing* (pp. 38:1–38:4). New York, NY, USA: ACM. https://doi.org/10.1145/2948910.2948959.
Kwon, Y., Lee, S., Jeong, J., & Kim, W. (2014). HeartiSense: A novel approach to enable effective basic life support training without an instructor. *CHI '14 extended abstracts on human factors in computing systems* (pp. 431–434). New York, NY, USA: ACM. https://doi.org/10.1145/2559206.2574801.
Lahanas, V., Loukas, C., Smailis, N., & Georgiou, E. (2015). A novel augmented reality simulator for skills assessment in minimal invasive surgery. *Surgical Endoscopy, 29*(8), 2224–2234. https://doi.org/10.1007/s00464-014-3930-y.
Lee, I.-J., Chen, C.-H., & Chang, K.-P. (2016). Augmented reality technology combined with three-dimensional holography to train the mental rotation ability of older adults. *Computers in Human Behavior, 65*, 488–500. https://doi.org/https://doi.org/10.1016/j.chb.2016.09.014.
Li, H., Lu, M., Chan, G., & Skitmore, M. (2015). Proactive training system for safe and efficient precast installation. *Automation in Construction, 49*, 163–174. https://doi.org/10.1016/J.AUTCON.2014.10.010.
Lin, C.-Y., Chen, C.-J., Liu, Y.-H., Chai, H.-C., Lin, C.-W., Huang, Y.-M., et al. (2015). Integrating motion-capture augmented reality technology as an interactive program for children. In M. Antona, & C. Stephanidis (Eds.). *Universal access in human-computer interaction. Access to learning, health and well-being* (pp. 149–156). Cham: Springer International Publishing.
Liu, J., Mei, J., Zhang, X., Lu, X., & Huang, J. (2017). Augmented reality-based training system for hand rehabilitation. *Multimedia Tools and Applications, 76*(13), 14847–14867. https://doi.org/10.1007/s11042-016-4067-x.
Lok, B., Chuah, J. H., Robb, A., Cordar, A., Lampotang, S., Wendling, A., et al. (2014). Mixed-reality humans for team training. *IEEE Computer Graphics and Applications, 34*(3), 72–75. https://doi.org/10.1109/MCG.2014.57.
Manuri, F., Sanna, A., Lamberti, F., Paravati, G., & Pezzolla, P. (2014). A workflow analysis for implementing AR-based maintenance procedures. In L. T. De Paolis, & A. Mongelli (Eds.). *Augmented and virtual reality* (pp. 185–200). Cham: Springer International Publishing.
Matassa, A., & Morreale, F. (2016). Supporting singers with tangible and visual feedback. *Proceedings of the international working conference on advanced visual interfaces* (pp. 328–329). New York, NY, USA: ACM. https://doi.org/10.1145/2909132.2926081.
McDaniel, M. A., Schmidt, F. L., & Hunter, J. E. (1988). Job experience correlates of job performance. *Journal of Applied Psychology, 73*(2), 327–330. https://doi.org/10.1037/0021-9010.73.2.327.
Meleiro, P., Rodrigues, R., Jacob, J., & Marques, T. (2014). Natural user interfaces in the motor development of disabled children. *Procedia Technology, 13*, 66–75. https://doi.org/https://doi.org/10.1016/j.protcy.2014.02.010.
van Merriënboer, J. J. G., Clark, R. E., & de Croock, M. B. M. (2002). Blueprints for complex learning: The 4C/ID-model. *Educational Technology Research & Development, 50*(2), 39–61. https://doi.org/10.1007/BF02504993.
Merrill, M. D. (2002). First principles of instruction. *Educational Technology Research & Development, 50*(3), 43–59. https://doi.org/10.1007/BF02505024.
Milazzo, N., Farrow, D., & Fournier, J. F. (2016). Effect of implicit perceptual-motor training on decision-making skills and underpinning gaze behavior in combat athletes. *Perceptual & Motor Skills, 123*(1), 300–323. https://doi.org/10.1177/0031512516656816.
Mura, M. D., Dini, G., & Failli, F. (2016). An integrated environment based on augmented reality and sensing device for manual assembly workstations. *Procedia CIRP, 41*, 340–345. https://doi.org/https://doi.org/10.1016/j.procir.2015.12.128.
Neelen, M., & Kirschner, P. A. (2016). *Deliberate Practice: What it is and what it isn't – 3-Star learning experiences.* Retrieved March 18, 2018, from https://3starlearningexperiences.wordpress.com/2016/06/21/370/.
Onishi, K., Mizushino, K., Noborio, H., & Koeda, M. (2014). Haptic AR dental simulator using z-buffer for object deformation. In C. Stephanidis, & M. Antona (Eds.). *Universal access in human-computer interaction. Aging and assistive environments* (pp. 342–348). Cham: Springer International Publishing.
Oyekan, J., Prabhu, V., Tiwari, A., Baskaran, V., Burgess, M., & Mcnally, R. (2017). Remote real-time collaboration through synchronous exchange of digitised human–workpiece interactions. *Future Generation Computer Systems, 67*, 83–93. https://doi.org/https://doi.org/10.1016/j.future.2016.08.012.
Park, K., Kihl, T., Park, S., Kim, M. J., & Chang, J. (2016). Narratives and sensor driven cognitive behavior training game platform. *2016 IEEE 14th international conference on software engineering research, management and applications (SERA)* (pp. 125–131). . https://doi.org/10.1109/SERA.2016.7516137.
Patterson, R. E., Pierce, B. J., Bell, H. H., & Klein, G. (2010). Implicit learning, tacit knowledge, expertise development, and naturalistic decision making. *Journal of Cognitive Engineering and Decision Making, 4*(4), 289–303. https://doi.org/10.1177/155534341000400403.
Perlini, S., Salinaro, F., Santalucia, P., & Musca, F. (2014). Simulation-guided cardiac auscultation improves medical students' clinical skills: The pavia pilot experience. *Internal and Emergency Medicine, 9*(2), 165–172. https://doi.org/10.1007/s11739-012-0811-z.
Prabhu, V. A., Elkington, M., Crowley, D., Tiwari, A., & Ward, C. (2017). Digitisation of manual composite layup task knowledge using gaming technology. *Composites Part B: Engineering, 112*, 314–326. https://doi.org/10.1016/j.compositesb.2016.12.050.
Radu, I., Doherty, E., DiQuollo, K., McCarthy, B., & Tiu, M. (2015). Cyberchase shape quest: Pushing geometry education boundaries with augmented reality. *Proceedings of the 14th international conference on interaction design and children* (pp. 430–433). . https://doi.org/10.1145/2771839.2771871.
Rane, P., Kim, H., Marcano, J. L., & Gabbard, J. L. (2016). Virtual road signs: Augmented reality driving aid for novice drivers. *Proceedings of the Human Factors and Ergonomics Society - Annual Meeting, 60*(1), 1750–1754. https://doi.org/10.1177/1541931213601401.
Rikers, R. M. J. P., Van Gerven, P. W. M., & Schmidt, H. G. (2004). Cognitive load theory as a tool for expertise development. *Instructional Science, 32*(1), 173–182. https://doi.org/10.1023/B:TRUC.0000021807.49315.31.
Roads, B., Mozer, M. C., & Busey, T. A. (2016). Using highlighting to train attentional expertise. *PLoS One, 11*(1), e0146266 https://doi.org/10.1371/journal.pone.0146266.
Rozenblit, J. W., Feng, C., Riojas, M., Napalkova, L., Hamilton, A. J., Hong, M., et al. (2014). The computer assisted surgical trainer: Design, models, and implementation. *Proceedings of the 2014 summer simulation multiconference* (pp. 30:1–30:10). San Diego, CA, USA: Society for Computer Simulation International.
Sand, O., Büttner, S., Paelke, V., & Röcker, C. (2016). smARt.Assembly – projection-based augmented reality for supporting assembly workers. In S. Lackey, & R. Shumaker (Eds.). *Virtual, augmented and mixed reality* (pp. 643–652). Cham: Springer International Publishing.
Sanfilippo, F. (2017). A multi-sensor fusion framework for improving situational awareness in demanding maritime training. *Reliability Engineering & System Safety, 161*, 12–24. https://doi.org/https://doi.org/10.1016/j.ress.2016.12.015.
Sano, Y., Sato, K., Shiraishi, R., & Otsuki, M. (2016). Sports support system: Augmented ball game for filling gap between player skill levels. *Proceedings of the 2016 ACM international conference on interactive surfaces and spaces* (pp. 361–366). New York, NY, USA: ACM. https://doi.org/10.1145/2992154.2996781.
Sara, C., Maria, V. R., Simone, F., Matteo, B., Luca, M., Mauro, F., et al. (2016). *Tactile augmented reality for arteries palpation in open surgery training.* https://doi.org/10.1007/978-3-319-43775-0_17.
Sarfo, F. K., & Elen, J. (2006). Technical expertise development in secondary technical schools: Effects of ICTenhanced 4C/ID learning environments. *Proceedings of the fourth IEEE international workshop on technology for education in developing countries* (pp. 62–65). Washington, DC, USA: IEEE Computer Society. https://doi.org/10.1109/TEDC.2006.25.
Schneider, J., Börner, D., van Rosmalen, P., & Specht, M. (2017). Presentation trainer: What experts and computers can tell about your nonverbal communication. *Journal of Computer Assisted Learning, 33*(2), 164–177. https://doi.org/10.1111/jcal.12175.
Sebillo, M., Tortora, G., Vitiello, G., Paolino, L., & Ginige, A. (2015). The use of augmented reality interfaces for on-site crisis preparedness. In P. Zaphiris, & A. Ioannou (Eds.). *Learning and collaboration technologies* (pp. 136–147). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-20609-7_14.
See, Z. S., Billinghurst, M., Rengganaten, V., & Soo, S. (2016). Medical learning murmurs simulation with mobile audible augmented reality. *SIGGRAPH ASIA 2016 mobile graphics and interactive applications* (pp. 4:1–4:4). New York, NY, USA: ACM. https://doi.org/10.1145/2999508.2999527.
Shekhar, R., Dandekar, O., Bhat, V., Philip, M., Lei, P., Godinez, C., et al. (2010). Live augmented reality: A new visualization method for laparoscopic surgery using continuous volumetric computed tomography. *Surgical Endoscopy and Other Interventional Techniques, 24*(8), 1976–1985. https://doi.org/10.1007/s00464-010-0890-8.
Sousa, L., Alves, R., & Rodrigues, J. M. F. (2016). Augmented reality system to assist inexperienced pool players. *Computational Visual Media, 2*(2), 183–193. https://doi.org/10.1007/s41095-016-0047-3.

Stunt, J. J., Kerkhoffs, G. M. M. J., Horeman, T., van Dijk, C. N., & Tuijthof, G. J. M. (2016). Validation of the PASSPORT V2 training environment for arthroscopic skills. *Knee Surgery, Sports Traumatology, Arthroscopy, 24*(6), 2038–2045. https://doi.org/10.1007/s00167-014-3213-0.

Such, M., Ward, C., Hutabarat, W., & Tiwari, A. (2014). Intelligent composite layup by the application of low cost tracking and projection technologies. *Procedia CIRP, 25*, 122–131. https://doi.org/https://doi.org/10.1016/j.procir.2014.10.020.

Sun, X., Byrns, S., Cheng, I., Zheng, B., & Basu, A. (2016). Smart sensor-based motion detection system for hand movement training in open surgery. *Journal of Medical Systems, 41*(2), 24. https://doi.org/10.1007/s10916-016-0665-4.

Tokuyasu, T., Okamura, W., Kusano, T., Inomata, M., Shiraishi, N., & Kitanou, S. (2014). Training system for endoscopic surgery by using augmented reality and forceps control devices. *2014 ninth international conference on broadband and wireless computing, communication and applications* (pp. 541–544). . https://doi.org/10.1109/BWCCA.2014.113.

Tong, Y., Wang, Y., Chen, J., & Chen, C. (2016). *A small scene assistant maintenance system based on optical see-through augmented reality. Proceedings of the 15th ACM SIGGRAPH conference on virtual-reality continuum and its applications in industry*, *Vol. 1*, New York, NY, USA: ACM155–158. https://doi.org/10.1145/3013971.3014021.

Van Merriënboer, J. J. G., & Kester, L. (2014). The four-component instructional design model: Multimedia principles in environments for complex learning. In R. Mayer (Ed.). *The cambridge handbook of multimedia learning* (pp. 104–148). Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781139547369.007.

Wang, X., Ong, S. K., & Nee, A. Y. C. (2016). Multi-modal augmented-reality assembly guidance based on bare-hand interface. *Advanced Engineering Informatics, 30*(3), 406–421. https://doi.org/10.1016/j.aei.2016.05.004.

Wei, Y., Yan, H., Bie, R., Wang, S., & Sun, L. (2014). Performance monitoring and evaluation in dance teaching with mobile sensing technology. *Personal and Ubiquitous Computing, 18*(8), 1929–1939. https://doi.org/10.1007/s00779-014-0799-7.

Western, C., Hristov, D., & Schlosser, J. (2015). Ultrasound imaging in radiation therapy: From interfractional to intrafractional guidance. *Cureus, 7*(6), e280. http://doi.org/10.7759/cureus.280.

Yarnall, L., Zhu, Z., Branzoi, V., Wolverton, M., Murray, G., Vitovitch, N., et al. (2014). AR-mentor: Augmented reality based mentoring system. *Mixed and augmented reality* (pp. 17–22). ISMAR. https://doi.org/10.1109/ISMAR.2014.6948404.

Zhao, Y., Salunke, S., Leavitt, A., Curtin, K., Huynh, N., & Zeagler, C. (2016). E-archery: Prototype wearable for analyzing archery release. *Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing: Adjunct* (pp. 908–913). New York, NY, USA: ACM. https://doi.org/10.1145/2968219.2968577.

Zhu, J., Ong, S. K., & Nee, A. Y. C. (2014). A context-aware augmented reality system to assist the maintenance operators. *International Journal on Interactive Design and Manufacturing, 8*(4), 293–304. https://doi.org/10.1007/s12008-013-0199-7.