Adaptive Instructional System for Complex Equipment Trainings in the Post-covid Era: Breaking the Ice of Time-Consuming Tasks

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Abstract. Complex equipment trainings frequently rely on in-person trainings to describe instrument parts and personalize explanations based on training objectives, prior knowledge, and cognitive abilities of trainees. In this study, we assess the main challenges of adapting intelligent instructional system by training centers with limited human and technological resources. We found that the preparation of the training material is the most time-consuming task. During the COVID-19 pandemic, many training centers were forced to remotely conduct their trainings, thus generating a massive amount of digital training content. Here, we explore this unique opportunity to recycle this training material to design an adaptive instructional system (AIS) for bioimaging training. In this paper, we discuss the functional features of AIS that facilitate autonomous training for trainees and instructors: progress bar, notification system, built-in teleconferencing, and chatting tools. To address a high level of customization of in-person trainings, we designed AIS trainings as module-based instructions that can be easily tailored to accommodate the objectives and needs of the trainees. We also demonstrate that modular design of the training material database accelerates allocation and preparation of training content for similar types of equipment. We set up a framework for implementing a recommendation system that would accommodate the training material to the trainee's experience. Our study shows that over the short or medium term, the potential of AIS solution for equipment trainings significantly outweighs the most time-consuming tasks like preparation of the training material.

Keywords: Adaptive instructional system · Equipment training · Personalized learning · Intelligent training

1 Introduction

Adaptive instructional systems (AIS) provide a great potential for increasing effectiveness and efficiency of trainings by better accommodating the needs and abilities of different learners (1). AIS development for equipment trainings is a separate area among intelligent training systems and is extensively studied as part of flight, driving simulators and trainings of power plant operators [2–7]. The initiative to adapt classical verbal

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in-person trainings towards more automated regimes in these areas comes from the strict requirements to high level of standardization of obtained knowledge and skills.

A very different dynamics of adaptation AIS can be observed in training environment driven by self-motivation of the trainees such as academic core facilities. Core facilities (CFs) represent a strategic part of the research infrastructure in universities, institutes and health centers that concentrate different types of scientific equipment (e.g., microscopes) shared between different research teams [8, 9]. Due to the high cost and complexity, all the equipment of the same type is centralized in dedicated entities like CFs, which provide routine maintenance and on-demand training services for these different equipment units. The limited labor force in CFs and high self-motivation of the trainees in on-demand trainings resulted in the lack of prerequisites for transitioning towards AIS-based trainings in CFs.

However, the COVID-19 pandemic forced training centers like institute/university CFs to conduct trainings remotely. While previous studies showed the great potential of introducing VR-based equipment trainings as a remote visual alternative [10, 11], it is not always possible to quickly adapt a VR solution for equipment trainings with limited human and technological resources. Due to the complexity and diversity of the equipment, CF provide 1-on-1 training sessions that are highly customized to the objectives, experience, and engagement of the trainees. Therefore, creating digital material for such sessions is a time-consuming task that is largely restrained by limited labor-force. During the pandemic, training centers like CFs completely stopped training new users during lockdowns and switched to teleconferencing type of trainings for existing users (a.k.a. verbal training) [12, 13]. This provided a unique opportunity to re-purpose the digital material created for visual support for remote trainings (photos of equipment parts) and videos of the controlling software recorded during the training sessions. The goal of this study is to design an AIS solution for 1-on-1 equipment trainings and to demonstrate its potential as a cost-efficient solution for next generation CF trainings.

To address this goal, we examine two research questions: (RQ1) What are the factors that can increase the cost-efficiency of adapting an AIS training solution (MicroAssistant) for equipment trainings without compromising its quality? (RQ2) How to personalize MicroAssistant AIS for different training objectives and levels of explanation to achieve better assimilation of training material (to prevent trainee from being overwhelmed and keep the trainee's attention)?

In this study, we explore the difficulties of adapting an autonomous training solution for equipment trainings in CFs. The first research question examines several features of the instruction system and training material designed to increase the reliability and performance of AIS equipment training solution. The second research question discusses an application of modular design to customize trainings based on the trainee's objectives and without exposing the trainee to unnecessary parts of the training. As a part of the training customization, we also implement a recommendation system that tracks the trainee's activity and suggests adjustments to the training material according to the experience level.

2 Material and Methods

2.1 Participants and Equipment

This study was conducted with students as trainees who intended to use CF equipment for their research projects. The instructor who participated in the trainings can be considered as an expert instructor. All participants signed an informed consent form describing the purpose and benefits of the study, stating that participation was voluntary. Their input was confidential, and they could withdraw from the study at any time. As an example of equipment units, we used Leica confocal microscope TCS SP8 equipped with 3 PMTs (Photo-Multiplier Tubes) and one hybrid detector (HyD) and Leica widefield microscope DM6 equipped with a motorized XYZ stage and two cameras for different acquisition regimes.

2.2 Training Quality Evaluation

The training quality was evaluated by the instructor using mixed methods after each training session, by assessing the quality of the microscopy images of the samples taken during the microscopy trainings and as a part of a post-training interview with a trainee.

2.3 Pre-training Form

A pre-training form asked the trainees to (i) explain planned imaging experiments, (ii) respond to questions assessing previous experience with other microscopes, and (iii) point to equipment functionalities they are interested in.

2.4 Instructor and Trainee Feedback Forms

We use the trainee feedback form to obtain Kirkpatrick Level 1 feedback on the different parts of training instructions, different functionalities of MicroAssistant, overall experience with MicroAssistant, and the will to continue using MicroAssistant for trainings on other imaging instruments (14). In addition, we use the instructor feedback form to obtain Kirkpatrick Level 1 feedback on different functionalities of MicroAssistant as well as the satisfaction with the single and double-training experience with MicroAssistant solution.

2.5 Software Architecture of MicroAssistant Platform

MicroAssistant is designed as a web application that can be accessed remotely through a browser by any authenticated account holder. The frontend client consists of a React application that uses Bootstrap for component design and styling, along with Redux and React Hooks for state management. It is serviced by an HTTP API created using Flask web-development framework. It is responsible for analysing and fetching all application data from the PostgreSQL database deployed on the server. Efficient data retrieval is implemented using standard Postgres indexing techniques (B-Tree indexes). The PostgreSQL database is used to store all metadata for a particular block/module/instruction. The storage and distribution of all visual resources is outsourced to a cloud service (Amazon Web Services).

2.6 MicroAssistant UI Design

MicroAssistant has 3 main components. A training interface also referred as the User Cabinet (Fig. 1), an instructor interface allowing to monitor the progresses of the trainees, and a training module manager allowing an administrator to edit and organize the training material.

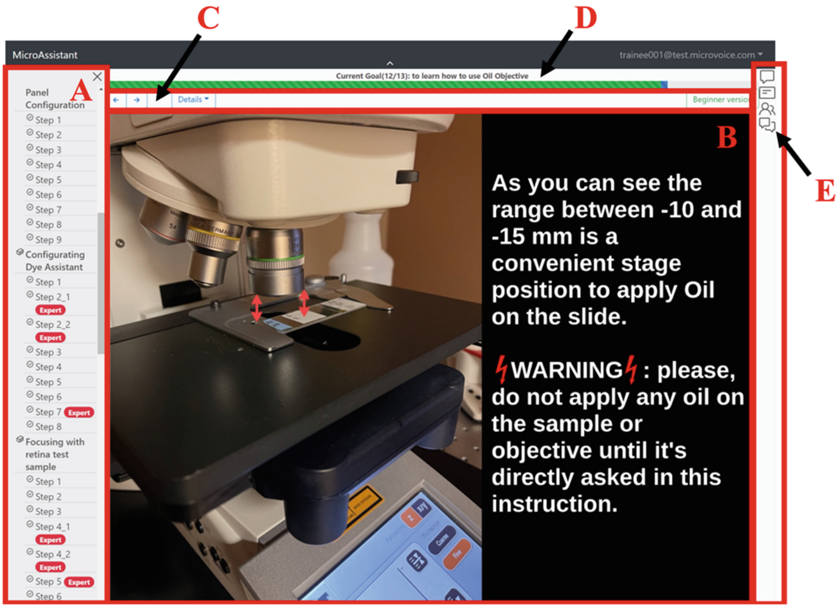

Fig. 1. Training interface of user cabinet. (A) The retractable sidebar with step-by-step training instruction. (B) The content placeholder displaying current training step. (C) The navigation bar with back/forward buttons and details section with supplemental training modules. (D) Progress bar with the current training goal and an overall training progress. (E) The tollbar with additional functionalities: notes, comments, external links, MicroTalk and MicroChat.

User Cabinet UI. The User Cabinet represents our training interface (Fig. 1). The retractable left sidebar (Fig. 1A) displays a tree-like view on the instruction in progress, where each step consists of a resource block with training content. The Content placeholder (Fig. 1B) is designed to occupy the central part of the screen and displays an instruction training step represented by an annotated image with (optional) audio support. The Navigation bar (Fig. 1C) includes Back and Forward buttons and a Details dropdown button including all the supplemental training modules that are referred to in the main instruction. The trainee can access information about the current goal and progression through the training material as a progress bar on the top panel (Fig. 1D). The toolbar on the right (Fig. 1E) provides trainee with additional functionalities of MicroAssistant: leaving notes (can be exported by the trainee at the end of the training), comments, external links, MicroTalk (a built-in videoconferencing tool to contact instructor directly) and MicroChat (a built-in chat with an instructor).

Progress (Instructor Monitoring) UI. A progress interface enables instructors to monitor in a real-time the progress of trainees. It highlights when a trainee approaches a training milestone, which requires additional instructor attention. It also displays comments left by the trainee and provides access to a built-in videoconferencing tool (MicroTalk) and chatting feature (MicroChat) (Fig. 2). The real-time functionalities mentioned above are enabled through the Socket.IO library which allows low latency, bi-directional communications between the multiple React frontend clients (instructor and trainees) and the Flask backend.

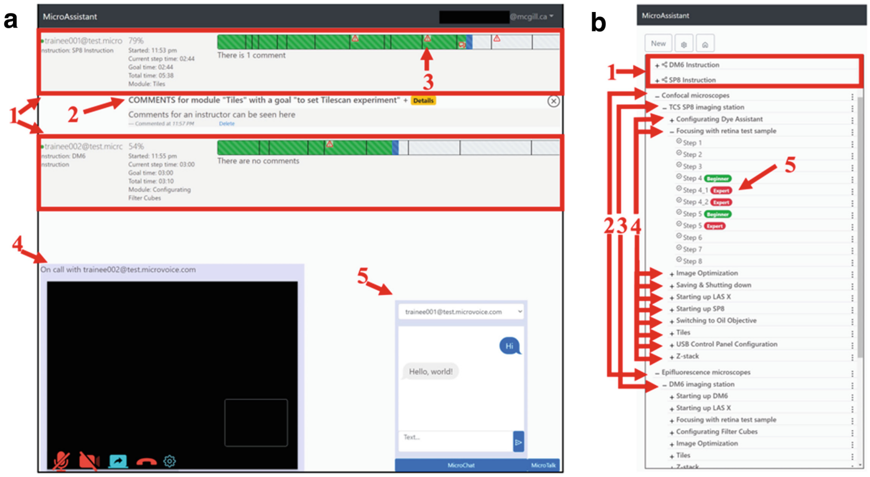

Fig. 2. Progress interface design (A) includes progress of different trainees (1), comments left by a trainee (2), marking critical steps (3), built-in teleconferencing tool (4) and chatting option (5). (B) training modules database includes instruction-type of blocks (1) and training material blocks sorted by type of the imaging equipment (2), microscope name (3), training subjects (4) and assigned with levels used by recommendation system (5).

Training Modules UI. The training material is composed of training modules, which are themselves consisting of series of several training steps. The database of modules was organized by type of the microscope, name of the imaging instrument, training subject explained inside of the module, and difficulty level (used by the recommendation system) (Fig. 3). To create a new training module, an instructor (or database administrator) needs to create new steps (or copy steps from pre-existing modules). Each step contains an annotated image (.pdf or.png file) and an optional audio file that is played to the trainee during the training session. By using fuzzy search tool, the instructor can rapidly navigate through the training database, select the necessary modules to form an instruction-type of block (i.e., instruction), and assign it to multiple trainees. Any module can be linked to multiple instructions or can be copied to be edited as a separate module. The modularity of the content creation facilitates assembly and reuse of modules across the training material database.

2.7 MicroAssistant Recommendation System

The MicroAssistant application tracks the trainee's actions during the course training session. The full list of actions tracked by MicroAssistant are shown in Table 1. User activity is recorded using the react-tracking NPM package and all tracking logs are persisted to the application's PostgreSQL database to analyze the triggering parameters for notification and recommendation systems.

Table 1. User actions that are identified by the tracking system

Action name	Description
Trainee-step-previous	User navigates to the previous step
Trainee-step-next	User navigates to the next step
Trainee-step-sidebar	User switches to another step in the sidebar
Trainee-mouse-idle	User's mouse stays idle for over a minute
Trainee-visibility-change	User switches to another browser tab/window
Trainee-toggle-sidebar	User opens or closes the instructions sidebar
Trainee-note	User opens or closes the notes section
Trainee-comment	User sends a comment to the instructor
Trainee-finish-instruction	User completes an instruction
Trainee-details-select-block	User selects supplemental module
Trainee-details-step-{…}	User navigates inside supplemental material
Trainee-details-return	User returns to the main instruction

The notification system activates when the trainee 1) is inactive on the MicroAssistant training platform for a significantly unusual amount of time (baseline established by the control group) or 2) expresses abnormal behavior by repeated switching between different training modules. Once triggered, the notification system displays messages to the instructor inside the Progress interface to alert about an unusual behavior.

The recommendation system uses the time spent by the trainee at each step (step-time) as the triggering parameter to adapt the instruction material. The baseline data for training levels (Beginner and Expert) were established for each instruction step based on 2 control Expert trainings. When Eq. (1) or (2) is satisfied respectively for n consecutive steps, the recommendation system suggests to the trainee leveled up (Eq. 1) or leveled down (Eq. 2) the training material (Fig. 3). After being upgraded to the Expert level, the trainee can at any time revert manually to the Beginner version in the Navigation bar (Fig. 1C). The number of consecutive steps were selected as the average number of steps in the instruction required to explain 2 different equipment functionalities ($n = 4$ for TCS SP8 instruction used in this study):

$$time_{\mathrm{i}} < avg_i + std_i \tag{1}$$

$$time_{\mathrm{i}} \geq avg_i + std_i \tag{2}$$

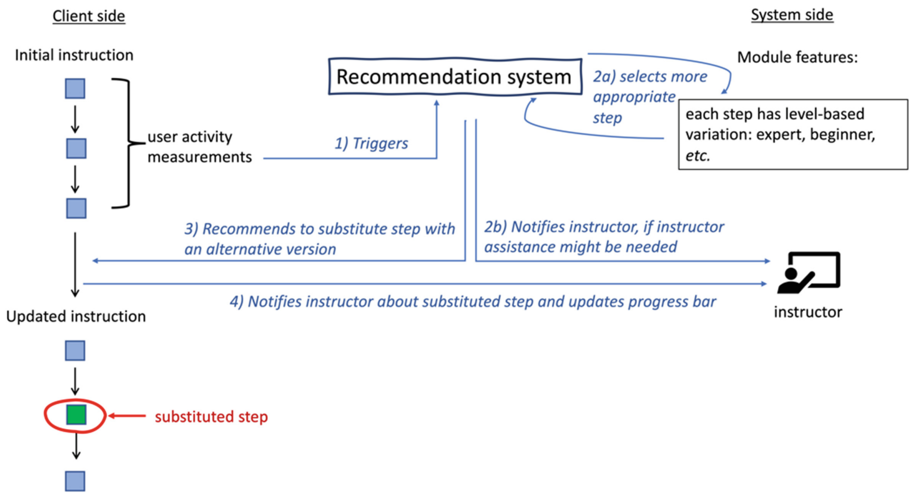

Fig. 3. Schematic design of the recommendation system and dynamic adjustments to the training instruction during the training session.

3 Results

3.1 Assessing the Difficulty of AIS Adaptation for Core Facilities

The main difficulty for training centers like CFs to automate personal trainings is to absorb the time-consuming task of preparing the training material. This study was conducted in collaboration with an institute bioimaging core facility that consists of 20 imaging instruments. The role of CF is to perform on-demand trainings (with an average of 200 trainings/per year) for all of these imaging instruments and ensure the operability of the equipment. All the trainings are performed in-person in 1-on-1 sessions to customize explanations to the trainee's objectives and level of expertise in bioimaging. Each training includes a theoretical part, hardware explanations, and a description of software functionalities and controls. However, each instrument has multiple functionalities. Each training is customized to only explain the necessary equipment features required to reach the objectives of the trainee. For example, using the same equipment unit, one trainee needs to be trained how to do 3D reconstruction of their specimen, while another trainee may need to do a 2D scan of the specimen. In this example, the instructor customizes the explanations to describe different functionalities of the equipment. Based on an interview with the instructor, digitizing the training material for one equipment unit would mean generating at least 3–4 versions of the instruction to address different objectives. This would require the instructor to generate 20–50 photos of equipment parts and up to 100 screenshots of the states of the software controlling the equipment unit, which would cost a prohibitive amount of time. In the interview, the manager of the core facility underlined that the cost-efficiency of preparation of training content for the facilities with limited labor-force would be too high to adapt autonomous trainings with an instructional system.

During pre-pandemic times, it was considered as a highly time-consuming task (i.e., to create digital instructions with a lack of hardware and software images), the necessity to assemble this material during the pandemic turned out to be a unique opportunity to re-use this digital content. When research laboratories were partially open, they implemented rotations and measures to prevent the accumulation of people in shared spaces. Then, core facilities made the photos of equipment locations and instrument parts to conduct the trainings remotely. We recycled this digital material as well as videos of the controlling software that were recorded during the training sessions to design a database of training modules.

Each module consists of a series of images (in PDF or PNG format) explaining one training topic and is designed to be followed step-by-step (Fig. 1). The preparation time for producing training modules for one imaging instrument (TCS SP8 microscope) took 20 h followed by 15 min for uploading them in MicroAssistant (Fig. 6A). This training content consisted of 12 training modules with 108 steps in the main instruction and 10 modules with 33 steps for supplemental information. Supplemental training modules were created to provide trainees with additional information on different topics. The whole training content for this instruction consisted of 85.1% the images derived from digital content created from pandemic remote trainings; 7.1% of images of the general theory and 7.8% of images for explaining navigation in MicroAssistant. We could not evaluate the cost-efficiency of creating training content as an isolated phase of AIS adaptation in CFs due to the lack of data of content preparation during pre-pandemic time (all the trainings were conducted in person at that time). Instead, we proceed in the evaluation of cost-efficiency of training content preparation as a part of the process of implementing of an AIS training solution for CFs.

3.2 RQ1: Different Tools to Overview and Intervene Training Sessions Reduces the Active Presence of the Instructor During Trainings with MicroAssistant

To evaluate the cost-efficiency of AIS adaptation in CFs, we first studied the factors that will increase the performance of MicroAssistant as a digital solution for equipment trainings. Based on the interviews with an instructor, we found that an important factor for the adaptation of an AIS in CFs is to increase the trackability of the trainee's activity for the instructor. Therefore, we designed tools that allows an instructor to monitor the training as needed. It includes 1) a progress bar allowing an instructor to access the trainee's progress and comments in real-time (Fig. 2A, 1); 2) a built-in chat and teleconferencing tools to communicate with the trainee during the training session (Fig. 2A, 4–5); 3) a warning system notifying the instructor and trainee of critical steps that must be followed to prevent possible damage to the equipment (Fig. 2A, 3); 4) a notification system tracking abnormal behaviour of the trainee (prolonged silence or jumping between steps) (Fig. 3). These features of the system made the training session more "transparent" and manageable, thus encouraging the instructor to proceed with autonomous trainings with the MicroAssistant AIS solution. Although, an instructor preferred to keep the remote desktop connection with the trainees, we observed a decrease in the time of active remote presence of the instructor during training sessions. Active remote presence was estimated as the active time the instructor spent on the Progress interface or the remote desktop connection to follow the trainee's actions. The trainings without progress bar showed that the instructor track the trainee's actions through the remote desktop connection 12.5% of the training session time (std = 3.5%, n = 2 trainings) (Fig. 4). After introducing in MicroAssistant the progress tracking system, teleconferencing tools, notifications and comments, the time of active remote presence dropped to 5.5% for the next 4 training sessions (std = 1%, n = 4 trainings). We conclude that the development of features to remotely track the progress and communicate with the trainee, as well as the implementation of a notification system facilitated the adoption of AIS-based trainings in CF, as it decreases the need for active presence of the instructor and therefore, increases the cost-efficiency of the MicroAssistant solution.

3.3 RQ1: Modular Design of Database of Training Content Decreases the Time for Preparation of Autonomous Trainings for Other Equipment

Another feature that increased the performance of MicroAssistant is the application of modular design principles to organize the training material. There are limited number of companies (Leica Microsystems, Nikon, Zeiss, Olympus) that produce bioimaging instruments with high resolution level (<180 nm) [15]. Thus, imaging stations in CFs often have similar parts and are controlled with similar software. As an example, we used the DM6 and TCS SP8 microscopes which both represent products of Leica Microsystems and are operated by Leica imaging software (LAS X). Although, the imaging properties and principles of image acquisition are very different between these two microscopes (DM6 is a widefield microscope with cameras for light detection; SP8 is a confocal microscope with special photon detectors), some parts of the microscope stand (touchpad, focus knobs) and some functionalities of the controlling software (tilescan, z-stack and project saving options of LAS X) are similar.

Structuring training material based on the training topics and storing them as modules with several steps allows to quickly search the necessary modules (using keyword search) and share training modules between the TCS SP8 and DM6 instructions. Training content for the DM6 microscope consisted of 9 modules with 83 steps in the main instruction and 8 modules with 16 steps in supplemental modules Two modules in the main instruction and 4 modules in the supplemental information (19.22% of training material) for the DM6 microscope were identical to the TCS SP8 training content (Fig. 5B, dark blue segment). Additionally, 34.03% of the steps of the DM6 main training content were adapted from similar steps in the TCS SP8 training material (Fig. 5B, light blue segment). DM6 training content preparation took 8 h followed by 15 min of uploading to MicroAssistant (Fig. 6A). We attribute such acceleration of content creation for DM6 to 1) the interchangeable properties of training content for equipment units in bioimaging facility, 2) the availability of templates from previous training material. The modular design of the MicroAssistant database of training content allowed us to significantly accelerate the time-consuming steps of training content preparation. Therefore, further increasing the cost-efficiency of the MicroAssistant solution.

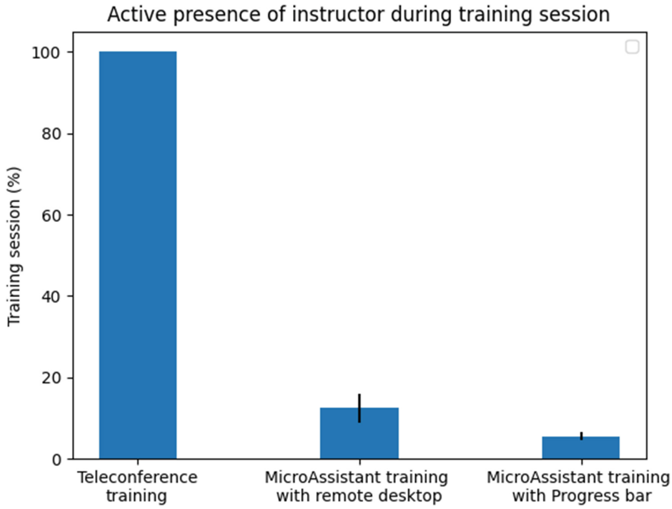

Fig. 4. Amount of time instructor actively interacts during teleconference trainings (100%), MicroAssistant trainings with remote desktop (12.5%, std = 3.5%, n = 2 trainings), with progress interface (5.5%, std = 1%, n = 4 trainings).

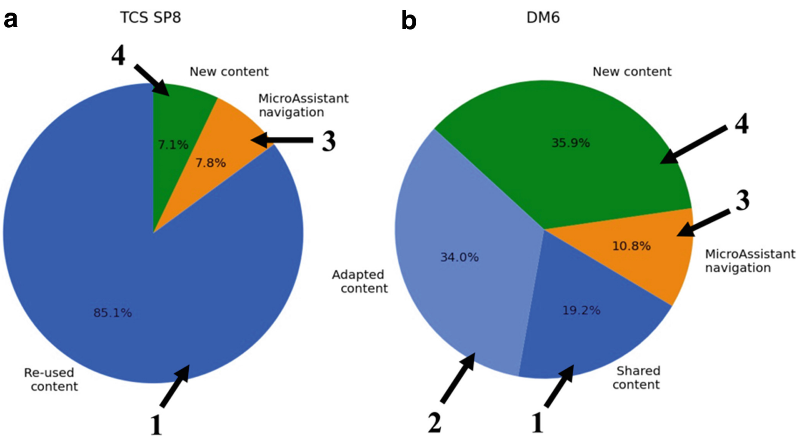

Fig. 5. Training content composition for TCS SP8 (A) and DM6 (B) microscopes. Re-used training material and shared modules indicated by dark blue (1), adapted training modules – by light blue (2), microAssistant program navigation modules – by orange (3) and newly created training modules – by green colors (4). (Color figure online)

3.4 RQ1: Introducing Simultaneous Trainings as a New Way to Increase Cost-Efficiency of Adaptation of Automatic Training Solution for Equipment Trainings in CFs

Simultaneous equipment trainings of users in CFs are only organized in the form of a separate training course. It is based on explaining and demonstrating to multiple trainees how to operate one type of imaging instrument. Such courses usually involve multiple copies of the same equipment units assembled in one room and arranged together with the institute or university and the equipment manufacturer. These trainings are conducted by one or a few instructors and are always organized as in-person trainings. The usual practice of equipment trainings in CF does not involve any aspect of simultaneous trainings, because imaging instruments in CF are never identical and often located in different rooms or different floors of the building.

In this study, we used the AIS training solution for training two equipment units simultaneously. The DM6 and TCS SP8 microscopes used in this study were physically located on different floors of the building and could not be used for simultaneous trainings during pre-pandemic in-personal trainings. Such double-training was also impossible to perform through verbal remote trainings conducted during the pandemic lockdown. By using the MicroAssistant step-by-step instructions, we set up 3 double-training sessions and the instructor was able to follow their progress in real-time (Fig. 2A). Trainees were unaware of the simultaneous aspect of their training session and rated the training experience as 5 out of 5 ($n = 6$ trainees). Based on the after-training interviews and instructor survey-form, the instructor did not notice a significant increase in active participation time per training (5%). However, there was a concern raised of a potential risk to accommodate 2 trainees in case of simultaneous emergencies with the equipment. The usual routine of remote desktop connection to the equipment computers does not support multiple connections at the same time. We suggest that additional double-trainings are required to test MicroTalk together with screen sharing options as a potential way to provide a trainee an immediate support. Therefore, we propose MicroAssistant AIS as a solution for potential simultaneous equipment trainings if there is a well-established connection routine for troubleshooting issues of multiple trainees.

3.5 Cost-Efficiency of AIS Training Solution for Equipment Trainings in CF

To evaluate the cost-efficiency of adapting the MicroAssistant solution for autonomous equipment trainings in CFs, we used time as a proxy of the cost. Our assumption is that either an instructor is also a designer of the training modules, or they are two staff members of CF with the same hourly wage. Using the TCS SP8 and DM6 microscope trainings, we calculated the cost-efficiency of using the MicroAssistant autonomous training solution instead of in-person verbal trainings. Based on the booking calendar of CF in 2018 and 2019, the standard in-person training session for TCS SP8 lasted 65.2 min ($std = 33.37$, $n = 29$ trainings) and for DM6, it lasted 50.7 min ($std = 29.3$, $n = 29$ trainings). We estimate that the trainings with MicroAssistant involved 5.5 min of the instructor's active involvement per training for both microscopes ($std = 0.55$, $n = 6$ trainings) based on time spent on following the trainee's progress. None of the trainings required an intervention of the instructor or direct communication with the trainees through teleconferencing tools. During double-trainings, we estimated that the instructor spent twice as much time to follow both trainees.

We define the efficiency of adaptation of MicroAssistant for equipment trainings as the time required for CF to liberate the necessary amount of instructor time during MicroAssistant-based trainings to be able to prepare training content for 1 equipment unit:

(Eq. 3).

$$CE = \frac{TF \times (DT - AP)}{(CP + CU)} \quad (3)$$

CE - Cost-efficiency of MicroAssistant solution per equipment unit (months $^{-1}$), *TF*- training frequency with MicroAssistant (trainings/year), *CP*- preparation time of training content, *CU*- time of uploading in MicroAssistant (15 min), *DT* – training duration for in-person training on that equipment unit, *AP*- time of active presence of the instructor.

We estimated the cost-efficiency of the MicroAssistant AIS training solution in 3 scenarios (Fig. 6B):

1. preparation of training content by re-using digital material from teleconferencing remote trainings (TCS SP8 example);
2. creation of training content using modular design of training content database created in the first scenario (DM6 example);
3. application of simultaneous training strategy for autonomous trainings with MicroAssistant (double-training example).

There was a dramatic increase in the cost-efficiency of MicroAssistant-based trainings for instructions prepared using a database of training modules from another equipment unit. After 11 in-person trainings on DM6 microscope, every next training with MicroAssistant will save ($DT-AP$) of instructor time. In case of double-trainings, it may double the cost-efficiency of the MicroAssistant solution per equipment unit (Fig. 6B) as it will allow to conduct twice as more trainings per calendar year. Based on the frequency of trainings for DM6 and TCS SP8 microscopes in 2018–2019 years (14.5 training/year), we estimate that the adaptation of the MicroAssistant instructional platform can be considered as a cost-efficient solution after 8.5 months. However, considering the advantage of conducting simultaneous autonomous trainings the cost-efficiency with double trainings using the MicroAssistant solution could be reached within 4.25 months.

3.6 RQ2: Modular Design Allows Rapid Customization of Training Session

One of the difficulties to adapt autonomous solution for equipment trainings in bioimaging CF was the nature of the multifunctional characteristic of the imaging equipment. This requires multiple versions of the trainings and therefore increases the time to prepare training material for autonomous trainings.

The modular design of the training content used in MicroAssistant allows the instructor to select only necessary training modules relevant to the objectives of the trainee. In this study, the trainee filled a Pre-training form with required information about imaging objectives and experiment needs. The instructor was selecting the required training material out of the database of training modules (through keyword search) and either assembling them in the new instruction or selecting pre-assembled versions of the instruction (Fig. 2B). Therefore, during the training session, the assigned trainee could access only the necessary training content. In this study, these steps were manually done by the instructor because selecting and assembling instruction takes less than 5 min and

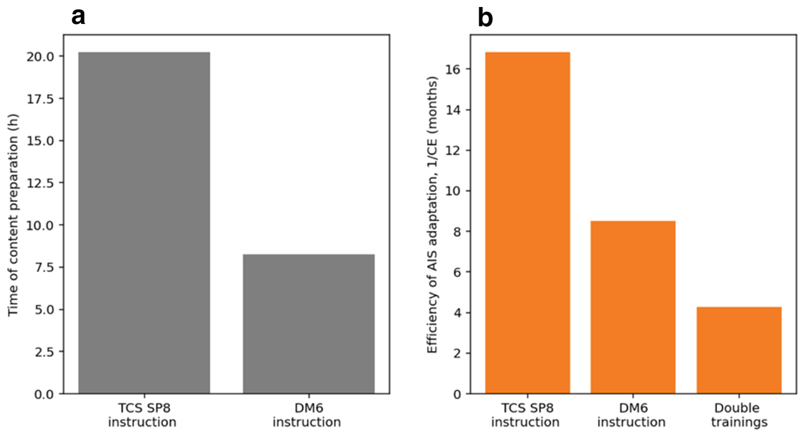

Fig. 6. Time required for training material preparation by creating training modules *de novo* (for TCS SP8 training) and by using training modules database (for DM6 trainings) (A). Time required for CF to reach cost-efficiency with MicroAssistant trainings in 3 scenarios: 1) creating training material by re-using digital material (TCS SP8 trainings), 2) creating training material by using database of training modules (DM6 trainings); 3) MicroAssistant application for double-trainings.

does not significantly change the cost-efficiency of MicroAssistant adaptation. However, upon further collection of pre-training form responses, we plan to automatize this step to reduce instructor involvement.

We used the TCS SP8 and DM6 microscopes as an example of the equipment units to build the training content. While 9 out of 12 modules were mandatory for operating the TCS SP8 microscope, the other 3 modules (A, B, C) and any of their combinations are included in the training according to the trainee's needs/objectives. Therefore, creating a modular database of the training content allowed the instructor to compose at once 7 different instructions that could include A, B, C, AB, AC, BC, or ABC modules. 7 out of 9 modules were mandatory for any training on the DM6 microscope, while including any combination of the 2 other modules could vary based on the trainee's needs/objectives. Therefore, the modular design allows instructors to easily customize trainings according to the different objectives of the trainee.

3.7 RQ2: Recommendation System Increases Engagement of Trainees During Autonomous Trainings

In-person trainings of equipment units in CFs are usually based on the objectives and experience level of the trainee with imaging instruments. To address experience level in AIS, we designed a recommendation system inside MicroAssistant. During the training, the recommendation system of MicroAssistant monitors the performance and engagement of the trainee by tracking the user activity (Table 1) and recommends the trainee to adjust the instruction according to their experience level.

In this study, we used TCS SP8 microscope for trainings with the recommendation system. We design the training content for 2 levels (Beginner and Expert) to include either more explanations of additional hardware and software functionalities (for Expert level) or more definitions and basic theory (for Beginner level).

First, based on the results of the Pre-training form, the trainee was assigned objective-oriented training modules that were also adjusted to appropriate experience/knowledge level. In our tests, all trainings included the same training objectives (ABC instruction version, described in Sect. 3.6). During the training, the recommendation system tracked the user activity (click tracker, mouse activity, timing the steps) and recommended adjustments to the instruction level accordingly (including training material in the main explanation and in supplemental materials) (Fig. 3). Due to lack of user base during this study ($n = 2$ trainings as a level control), we could not do a pattern analysis of trainees' behaviour to set up baseline for the different levels. Instead, we used as a threshold to trigger the recommendation system the time spent by a trainee per step. If, for 4 consecutive steps, the step time of the trainee was in the range of the step-time for those steps for another level, the recommendation system suggested to the trainee to adjust the instruction by leveling up (Expert) or leveling down (Beginner) the training material. If the trainee followed the recommendation, MicroAssistant modified the current instruction with training modules and supplemental information that corresponded to the new level.

We conducted 2 trainings with the recommendation system. Both trainees were previously trained in-person on the TCS SP8 microscope and were going through a re-training process. Despite expert level assignment by the Pre-training form, to minimize the risk of equipment damage during the testing of the recommendation system, we set all users to start the trainings as Beginners. Trainee 1 accepted the initial suggestion of the recommendation system to switch to Expert level after 16.7% completion of the training (Table 2). However, after multiple instruction restarts due to wi-fi network issues, the trainee denied afterwards to switch to the Expert level and finished the training as Beginner. Trainee 2 accepted levelling up to Expert level after 13.9% from the beginning of the instruction (Table 2); however, trainee 2 reverted multiple times to the Beginner level manually. Based on the comments of trainee 2, we attribute such behaviour to the trainee curiosity to check both versions of some modules. As indicated by the post-training feedback form, both re-trained users found some of the level-adjusted modules to be useful/new for them. Trainee 2 also found useful the Expert parts of supplemental topics. Both trainees appreciated the initiative of an autonomous training and rated the overall experience as 4 out of 5. Therefore, we conclude that adjustments to the training material through the recommendation system increased the engagement of trainees by providing useful training material for re-trained and new users. However, to improve the experience of the re-trained users, we suggest further customization of the training material that will reduce the mandatory parts of the training. We also propose further testing of the recommendation system with inexperienced users to establish the baseline behaviour of the control groups for each level.

3.8 Feedback-Based Evaluation of the System

Based n the results of the Feedback forms and after-training interviews, the overall training experience with MicroAssistant was evaluated as 4.7 out of 5 ($n = 9$ users). 75% of trainees expressed a wish to be trained with MicroAssistant for other imaging

Table 2. Summary of MicroAssistant trainings with the recommendation system

Performance of the recommendation system	Trainee 1	Trainee 2
Training duration (min)	89	72
Recommendation system first triggered at (% of instruction)	16.67%	13.89%
Recommendation system accepted (number of times)	1	4
Recommendation system denied (number of times)	7	1
Manual switching between levels (number of times)	0	3
Restarting instruction	4	0
Number of useful/new topics recommended by MicroAssistant	1	2
Overall experience evaluation (out of 5)	4	4

instruments. The main advantage of the system reported during interviews were: 1) an opportunity to follow the training in a self-paced manner; 2) an opportunity to learn equipment functionalities autonomously rather than observing instructor's actions during in-person trainings; 3) it was easy to follow organisation of training material. The main concerns raised by re-trained users were related to the big volume of the training material. We attribute such responses to the misfitting of Expert level training material for re-training sessions and propose in the future to prepare for re-training users a separate experience level. The instructor appreciated the elevated level of standardization in AIS trainings versus in-personal trainings but raised concerns regarding MicroAssistant trainings with trainees that are completely novice in microscopy. The instructor feedback included an appreciation of the reduced active time during MicroAssistant trainings, although pointing to the challenges of remote trainings that may rise in case of equipment failure.

4 Discussion

In this study we assessed the difficulty of introducing an AIS for equipment trainings conducted by training centers like CFs. Due to the complexity and diversity of the equipment, CFs usually provide 1-on-1 verbal training sessions that are highly customized to the objectives, experience, and engagement of the trainees. Therefore, creating digital material for such sessions is a time-consuming task largely restrained by the limited labor-force.

By re-using the digital material created for remote trainings during the pandemic lockdown (photos of equipment parts and videos of training sessions), we could create a database of training modules and design the AIS solution (MicroAssistant) for autonomous trainings. This study demonstrates that the material created in the aftermath of the pandemic offers a unique opportunity to assemble digital content created during COVID-lockdowns and to implement AIS in a field where its previous adaptation was not considered as cost-efficient. Based on our experience of developing AIS-based trainings for bioimaging CFs, we see a new post-pandemic potential for adaptation of

AIS training solutions in other different fields with complex equipment trainings (e.g., manufacturing operators, heavy equipment operators) [16, 17].

Despite time-consuming and labor-intensive tasks of training content preparation, we show that similarities between equipment units significantly facilitate the preparation of the training material (Fig. 6A), increasing the cost-efficiency of applying an AIS solution for CF trainings (Fig. 6B). Based on the limited number of manufacturers of imaging equipment, we anticipate that even greater similarities can be observed between different academic and medical bioimaging CFs as they operate with similar types of imaging instruments. This should even further facilitate the preparation of training material. Therefore, we suggest that AIS adaptation for medical and bioimaging training centers can be accelerated once the MicroAssistant training database reaches a higher level of diversification of training material and becomes able to accommodate the most common types of equipment and operating software.

To address the high level of personalization of in-person trainings, we designed MicroAssistant trainings as module-based instructions that can be easily altered to accommodate the objectives/needs of the trainees. We also developed a customization solution for different expertise levels of the trainees. The high self-motivation characteristic of trainees in CF allowed us to design an adaptive part of MicroAssistant based on recommendations proposed to the trainees by the tracking system. Once triggered, it provided an option to adjust the instruction with more relevant training content to the trainee's experience. Due to the small number of control training sessions for Expert and Beginner levels, we could not apply any probabilistic learner models (e.g., Bayesian Networks) for behavioral pattern analysis of the trainees [18, 19]. Instead, we used step-time as a parameter to trigger the recommendation system. Although MicroAssistant trainings with the recommendation system were part of a re-training initiative, all trainees appreciated and found useful the training material provided by the recommendation system (Table 1). Therefore, we conclude that the recommendation system is a useful tool to personalize equipment trainings. We expect that the continuous use of the MicroAssistant AIS will provide a more extensive user base and will allow further developments of the triggering conditions of the recommendation system.

Another advantage of using the MicroAssistant AIS for equipment trainings is the possibility of conducting simultaneous trainings by the same instructor. The progress bar and the built-in chat and teleconferencing tools provide an instructor with an overview of the progress of the trainee and facilitate remote communication if needed. Our study showed that the overall active presence of instructor per trainee did not increase during simultaneous trainings. Notably, all new trainees expressed interest in being trained with MicroAssistant for other imaging instruments. Based on our experience with double-trainings, we propose that the MicroAssistant AIS solution can introduce a new practice of simultaneous equipment trainings. However, we also conclude that simultaneous trainings require the development of a robust way to access multiple equipment computers remotely for troubleshooting if equipment issues arise at the same time.

The MicroAssistant AIS received positive evaluations from CF through an instructor feedback form, instructor interviews and trainee feedback forms (4.7 out of 5, n = 9 users). We attribute a successful user perception of AIS trainings to elevated self-motivation of the trainees in acquiring new skills.

5 Limitations

There are several limitations that must be considered in this study. First, the trainees in theses study already had some experience with other imaging equipment in CF. Therefore, they were not completely novice to the use of microscopes. Due to the potential risks of damaging the equipment, we could not test our autonomous training solution with first-time users. Second, this study used mixed methods to evaluate the quality of the training with MicroAssistant resulting in a lack of standardized evaluation of the results of the trainings. The on-demand trainings of self-motivated trainees prevents CFs from introducing routine after-training knowledge tests (i.e., it cannot be run as an exam). Third, the instructor concerns regarding simultaneous troubleshooting with MicroAssistant need further assessment with the potential implementation of simultaneous remote desktop connections. Additionally, this study does not reveal the full potential of the recommendation system for equipment trainings. Due to the lack of control trainings that would establish a baseline behaviour of trainees from distinct experience groups, we could not fully utilize the tracked user activity to set up a more advanced triggering mechanism for the recommendation system. Our focus was more concentrated on addressing the time-consuming tasks of training content creation as the main barrier for adaptation of AIS for equipment trainings in training centers with limited labor forces.

6 Conclusion and Future Directions

The results of this study show that, in the aftermath of the pandemic, there is a greater potential for designing AIS solutions for equipment trainings than before. By processing the digital content created during pandemic remote trainings, we designed the MicroAssistant AIS training platform for equipment trainings. We implemented MicroAssistant for bioimaging trainings. Based on our results, we conclude that MicroAssistant-driven trainings can be an efficient way to provide autonomous personalized equipment trainings if 1) the most time-consuming task (preparation of training material) is minimized by providing baseline training modules for equipment units, 2) the design of AIS enables the instructor to remotely monitor the training and getting notified in case of “abnormal” activity of a trainee, 3) the adaptive part of the AIS can provide trainee with only the necessary explanatory information.

In the future studies, we propose establishing an open-source training database for different medical and bioimaging CFs that could represent the source for training material for different imaging instruments. This should presumably further facilitate the adaptation of AIS for equipment trainings.

Another consideration for the future of the MicroAssistant solution is the development of its ability to adapt the training content to the expertise and motivation of the trainee. First, more reference trainings will need to be conducted with trainees deemed as Experts by the CF instructor as well as Beginner trainees. This further testing will help construct a better model of the differences between the distinct experience levels of CF trainees. Once the reference training data is gathered, we could apply a variety of learner models to characterize the behavior of a trainee in real-time. Probabilistic learner models (e.g., Bayesian Networks) and machine learning based models including

Deep Neural Networks [18, 19] could also be used by the recommendation system to analyze the trainee's activity and alter training material if needed. Additionally, we can also explore cognitive modelling methods like ACT-R to extract a more comprehensive and interpretable model of the trainee behavior in real-time [20].

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