Interaction and interface design for Primary Ciliary Dyskinesia annotation tool

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Abstract

Artificial intelligence (AI) has become a key tool in various fields, including medicine. AI models can effectively analyze cytological medical imagery data for Primary ciliary dyskinesia (PCD) diagnosis. This is multi-class classification problem, where each cilium is assigned a specific defect and dynein type. These models support doctors in their daily work and speed up their routine tasks. The goal of our research is to propose a methodology that optimizes the interaction between domain expert (DE) and AI in the field of histopathology through an innovative interface design. To achieve this, we focused on user experience (UX) and usability in medicine. Based on the state-of-the-art in the field and case study with DE in the field of PCD diagnostics, we designed a user interface to assist histopathologists in diagnosing PCD. To achieve our goals, we propose a modified Domain-Expert-Centered Double Diamond design methodology (DEDDM). Using our proposed DEDDM model, we designed a prototype of medical imagery annotation tool for PCD that meets the needs of experts working under time constraints. The annotation tool is designed to support manual annotation flow, as well as future integration of AI which will make DE's workflow even more efficient. We preliminary evaluated the design prototype, during which we identified 12 usability issues. After familiarizing themselves with the application layout, participants found it intuitive and pleasant to use. However, they initially faced difficulties understanding the interaction concept of creating manual annotations.

Keywords: Usability, User experience, Histopathology, Annotation tool

1 Introduction

Histopathology is a medical field centered on examining tissues and cells under a microscope to diagnose diseases. Histopathologists analyze small tissue samples obtained via biopsies from various organs to identify cellular changes that indicate specific diseases [7]. The disease in the focus of this paper is PCD. PCD is a genetically heterogeneous disorder that causes inflammation of the airways. This disorder is caused by an abnormality in the motility of the cilia, which are responsible for clearing the airways [3]. Currently, no standardized or heavily used digital tools exist which could help histopathologists in their PCD diagnostics workflow. Therefore, we address this challenge in this paper.

Diagnosing PCD is a time-consuming manual process that proceeds as follows. First, the histopathologist selects images of each cilium and uploads them to the program. Then they start marking the cilias. This process is called *annotating*, and each annotation consists of the type of microtubular defect (indicated by color) and dynein arms (indicated by mark). After annotating at least 100 cilia, with 50% evaluated for dynein, the histopathologist looks at the percentage of defective cilia out of those evaluated. If the defect falls into the first class, it indicates that the patient has genetic PCD.

The main contribution of this paper is the presented case study on designing the user interface for the novel and the only easily usable annotation tool for PCD diagnostics currently present. We proposed and validated our proposed DEDDM design framework specific for communicating with DE in a time-constrained manner. The outcome is the design of the user interface in the form of a ready-to-implementation prototype of an annotation tool for PCD diagnostics that meets all DE's requirements and will be suitable for international usage. The tool also forms a solid base for later AI integration.

In Section 2, we present the the state-of-the-art in digitalized histopathology and analyze existing tools in Section 3. In Section 4, we introduced our approach which we describe as a case study in Section 5. We then evaluate the results in Section 6 and discuss future work in Section 7.

2 Related work

Firstly, we focused on research state-of-the-art related to digitalized workflows for advanced and efficient diagnos-

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tics in histopathology. Then, we highlighted the key challenges in such a tool design and the design methods. Finally, we reviewed similar state-of-the-art tools used by histopathologists to inspire our contribution.

To ensure the adoption and use of AI tools by DEs, it is necessary to include them in the design process. However, the classic Human-Centred Design (HCD) process is not sufficient in this situation. Vishwarupe et al. [10] proposed a modified HCD process, called AI-HCI Confluence Framework, in which all phases are aligned with the training and modeling level of deep learning algorithms. Phases include the involvement of DEs and stakeholders. The prototyping phase is augmented by the Explainable AI, which helps build trust [10]. But even with a well-designed tool, integrating AI into histopathology has other challenges.

There are a few papers focused on AI-assisted applications for the histopathology domain [9, 5, 4, 2, 8]. Laak et al. [9] and Kim et al. [5] review current trends in Computational Pathology and its potential use in clinical practice. These applications automate time-consuming tasks, provide complementary information, seek to improve diagnostic accuracy, and reduce variability in pathology practice. However, there are many challenges associated with obtaining the necessary annotations for large datasets. Obtaining manual annotations is very challenging due to the time, cost, and repetitive work of experienced pathologists [9, 5]. For this reason, several approaches have been proposed, including increasing the number of expert annotators. Kim et al. support the fact that a large number of high-quality annotations need to be obtained and describe another possibility to gain them - online crowdsourcing [5] which involves people with different levels of expertise in the annotation process, with their work eventually checked by experts. Another method to simplify manual annotation is the weakly supervised learning method [9, 5].

Huss and Coupland [4] discuss how the implementation of AI in the field of histopathology can lead to significant progress in addressing clinical challenges. As previous works, it also analyzes the challenges and limitations of integrating AI due to the volume of training data. It emphasizes the challenge of understanding and ensuring the credibility of the results generated by the software, highlighting the need for transparency in training deep learning models. Additionally, it reminds that while automated software solutions in histopathology can be highly efficient, comparing them directly to pathologists might not be appropriate. Pathologists and computers should collaborate and leverage their respective strengths to address challenging tasks effectively.

Histopathologists are nowadays able to choose from a variety of annotation tools in their work and while some of them are user-friendly, most of them are not. However, none of them is tailored specifically for a very distinctive workflow of PCD diagnostics in the means of good usability. Carpenter et al. [2] focused on the usability issues of bioimaging software and defined criteria that should be met [2]. Another criterion of a tool using AI is the explainability of the output. Sabol et al. [8] developed a model for cancer diagnosis from histopathological images, incorporating AI decision explainability methods. They provided semantic reasoning and examples of Similar and Typical cases. When they tested the system with explainability and the system without it, the pathologists found the system with explainability to be more trustworthy, accurate, and complete [8].

3 Analysis of existing tools

Histopathological annotation tools fall under the image annotation category but they can vary in terms of task specificity, level of automation, integration, or collaboration features. We propose a division into two main groups: *general* and *specifically targeted*. General annotation tools are versatile and designed to handle a wide range of medical tasks within a single application. On the other hand, specifically targeted tools are focusing exclusively on the unique requirements of diagnosing or researching that specific disease. One general software tool is **QuPath**. QuPath is an open-source software application designed for analyzing and exploring whole slide images with annotation and visualization tools [1]. **PCD Quant** (Figure 1) is the only known specifically targeted annotation tool for the analysis of the cilia to diagnose PCD. The tool provides automatic cilia evaluation using deep neural networks [3]. There is also a tool under development at the Faculty of Informatics and Information Technologies STU in Bratislava, **Annotaid** (Figure 2), designed for the basic histopathology annotation workflows [11].

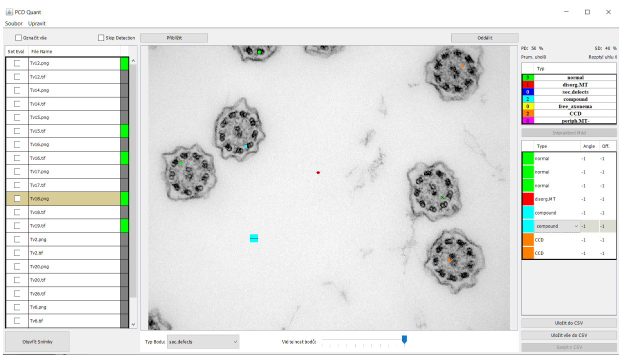

Figure 1: The user interface of the PCD Quant consists of a navigation with tools, a left sidebar with a list of annotations, and a right sidebar with information about the image or annotation. In the center is an annotated image.

To evaluate PCD Quant we performed an evaluation based on heuristics by Jakob Nielsen [6]. Through our heuristic evaluation of the PCD Quant tool, we identified 6 usability issues. The tool's visual appearance seems outdated and incomplete, which is not intuitive, lacks standard image zooming and documentation, provides no error

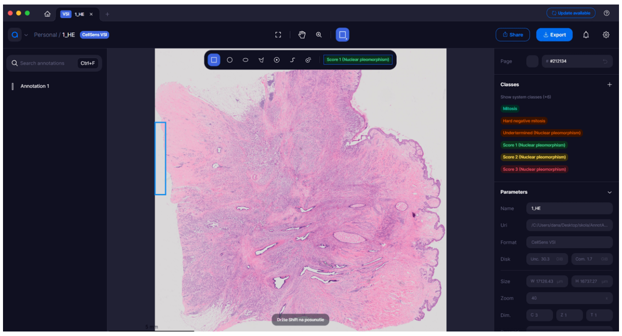

Figure 2: The user interface of the Annotaid consists of a navigation with tools, a left sidebar with a list of annotations, and a right sidebar with information about the image or annotation. In the center is an annotated image.

or status messages, and has inconsistent language. QuPath does not have all these problems - it provides a modern and friendly user interface, extensive documentation, and standard zooming, which makes it easy to use. However, its biggest drawback is excessive complexity. It provides far too many features and annotation options that cannot be hidden. This can be a problem for pathologists dealing with specific problems, such as PCD, as redundant functionality can distract and frustrate their attention. Annotaid also lacks some essential features for PCD diagnosis and includes functions that are not relevant.

4 Domain-Expert-Centered Double Diamond design methodology

To achieve the contributions outlined in the Section 1, we have to design a user interface. Creating a usable and pleasant annotation tool requires effective communication with DE. To ensure this communication is successful, it is important to follow a design methodology, such as the Double-Diamond Model. However, we have identified several issues that we will address during the design process:

- Our annotation tool is designed for DE in histopathology who is time-constrained and busy with important tasks. For this reason, the possibility of iterative prototype testing will be limited.
- Another annotation tool Annotaid is being developed specially for DE. To ensure consistency and minimize the learning curve, the design of the new tool should align with Annotaid. This approach will make the tool more intuitive and easier for DE to adopt without requiring significant retraining.
- The annotation tool may increase efficiency by augmenting or automating DE workflow using applications of the existing AI algorithms. DE needs to understand the AI outputs even without a deeper understanding of AI. Therefore, ensuring explainability and involving DE in their designs is necessary.

For these reasons, we propose a Domain-Expert-Centered Double Diamond design methodology, a modification of the Double Diamond Model that will focus on the DE-Doctor. This modification will mainly focus on efficiency while minimizing the need for communication with DE. The proposed framework is shown in Figure 3 and consists of the following phases:

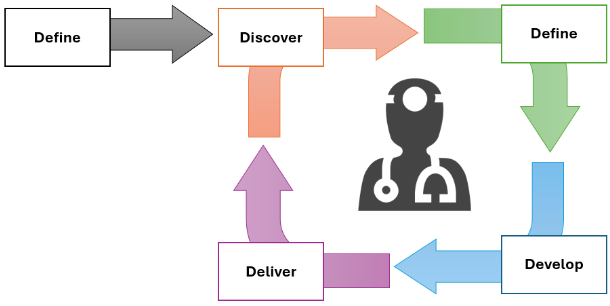

Figure 3: Phases of proposed DEDDM methodology.

1. In the first phase Define, **we analyzed the existing annotation tools** PCD Quant and Annotaid with the aim of identifying potential problems, workflows and necessary parts of the UI.
2. In the Discover phase, we conducted **user research with DE** to gain a deeper understanding of the issues and observe their workflow.
3. In the second phase Define, additionally, we identified the **AI approach** to problem-solving by determining how AI can assist DE.
4. In the Develop phase, aspects of the **prototype** were incorporated from existing tools and gathered information.
5. In the Deliver phase, we evaluated the prototype using a **usability testing**. To accommodate the limited availability of DE, we first conducted usability tests on **lay users**, simplifying the task to a universally understandable topic due to the complexity of PCD.

5 Case study

In this section, we describe the case study on application of DEDDM framework we proposed in Section 4. We discuss each phase in detail, along with the specific steps taken within it. In our case study, we were in contact with one domain expert from the Institute of Clinical and Experimental Medicine in Prague, who focuses on the field of histopathology and performs a full spectrum of diagnoses, along with PCD, by analyzing images of patient biopsies in digital form.

5.1 Define phase - Analysis of tools

In the first Define phase, we analyzed the existing annotation tools that DE uses or will use - PCD Quant (Figure 1) and Annotaid (Figure 2). We decided to inspire our proposal and keep crucial consistency with their design so that DE would not have to operate a completely new interface. Problems with these tools were described in Section 2.

5.2 Discover phase

To best understand the issues with annotation tools and the current state of the PCD field, we needed insights from DE. To obtain this information, we participated in three interviews with DE. First interview was aimed at observing DE's workflow and finding out information about the current state of the art in the field of PCD. The goal of second interview was to clarify the functional requirements and to get opinions on displaying AI functionalities in the prepared prototype. The goal of third interview was to clarify the workflow and system requirements from previous interviews to see if anything had changed after nearly a year, as this is an ongoing project.

5.3 Define phase

We used the knowledge gained from the interviews to understand the problems faced by DE. We defined personas, user scenarios, user flows, information architecture, and system requirements which will help us in the next stages. We also proposed AI approach which will be used in future work.

5.3.1 Personas

Based on the user research, we created two personas that will be the target users of the prototype. The first persona in Figure 4 is based on our DE - an experienced professional with many years of experience in histopathology and the use of annotation tools. During the first interview, DE mentioned that they would appreciate help from a university student who would annotate the images for them, while DE would only check them. Based on this, we proposed a second persona in Figure 5 - a beginner who is inexperienced with annotation tools and is concerned about possible errors.

5.3.2 AI approach

The interviews with DE revealed that the biggest benefit of AI would be **assisting in annotating the images**, especially in assigning dynein and defects to individual cilia.

AI will be simulated through **automation**, not augmentation. The main reason is that it is a manual and time-consuming process during which DE wants to minimize the need for clicks. An augmentation approach would not free the user from manual clicking, as they would still have to go through all the suggestions and select the right

Figure 4: Persona 1 - Expert. On the image is information about the persona Mariana, an experienced histopathologist, her goals, frustrations, and expectations.

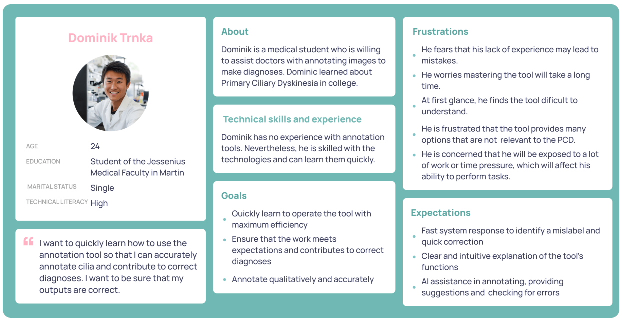

Figure 5: Persona 2 - Student. On the image is information about the persona Dominik, an inexperienced student of medicine, his goals, frustrations, and expectations.

one. For this purpose, the number of cilia and images is too large to process one by one. Automation also enables faster dataset creation for AI training.

AI model should also be optimized for **precision**. We asked DE whether this would suit them, and they responded that they would be more efficient at correcting fewer defective labels while completing the rest. Therefore, it is better to display fewer correctly labeled cilia, which the user will not have to edit afterward.

5.4 Develop phase

During the Develop phase, we designed a prototype that addressed identified user needs and was tailored to personas to execute defined scenarios. The prototype development occurred in 3 iterations described in the following sections. The final prototype can be seen in Figure 6.

Conventional prototyping tools were unsuitable as they lacked the degree of interactivity and credibility needed to support annotating functionalities. Therefore we implemented it using the JavaScript framework Vue.

An actor	Dominik
A motivator	The need for an accurate diagnosis whether PCD is genetic or due to another cause
An intention	Annotation of images to confirm the presence of defective cilia
An action	Dominic opens the program and uploads the images in TIFF format obtained from the patient's biopsies. He carefully analyses each image and assigns the type of microtubular defect and the type of dynein arms to the cilia. If he finds a specific abnormality, he may write a note on the project or image. After marking a sufficient number of cilia, he reviews the statistics to make a diagnosis.
A resolution	Dominic checks the calculated statistics and determines if PCD is genetic or not.

Table 1: User scenario 1: Dominik determines the diagnosis

An actor	Mariana
A motivator	Ensuring accurate diagnosis
An action	Mariana opens the project that was sent to her for review. She examines each annotated image and reviews the marks that have been made. If she finds an incorrect annotation, she corrects the type of defect or dynein. If necessary, she corrects or adds annotations.
A resolution	Mariana checks if the new stats result matches the original one. If not, she re-establishes the diagnosis.

Table 2: User scenario 2: Mariana reviews the project

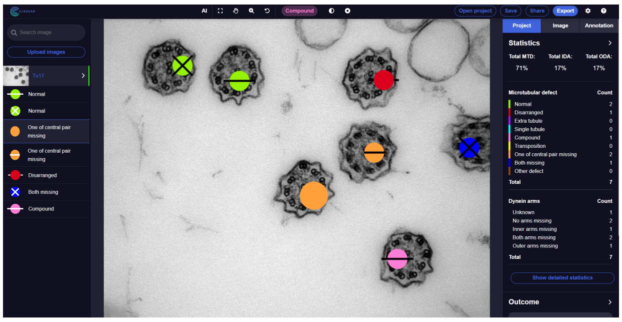

Figure 6: The user interface of our prototype CiliaScan consists of a navigation with tools, a left sidebar with a list of images and their annotations, and a right sidebar with information about the project, image, or annotation. In the center is an annotated image.

5.4.1 First iteration

In the first iteration, the prototype was designed based on the findings from the first two interviews and from the analysis of existing tools. The prototype design was primarily inspired by the visual style of the Annotaid, incorporating elements from PCD Quant. Firstly, we implemented the basic layout of the application which consisted of a navigation bar, left and right sidebars, and a main window for annotations. We also implemented basic functionalities for annotation (adding and editing annotations), uploading images, adding new defect classes, and image manipulation features such as zooming and dragging.

5.4.2 Second iteration

In the second iteration, the prototype was changed based on insights gained from the third interview. We made several enhancements to improve the overall UX alongside prototype adjustments. These include tutorials that explain the application layout and manual annotation process; Documentation and Settings; Detailed statistics with graphical visualizations; and options for data collection permissions and feedback questionnaires which provide both implicit and explicit feedback, supporting the continuous improvement of the application. This prototype was tested in layman usability testing.

5.4.3 Third iteration

The third iteration addressed usability issues from layman testing. Modal windows were added to prevent accidental actions (e.g., deleting images, removing annotations). Temporary alerts now inform users of system status and tool usage. These changes addressed the heuristics of *Error Prevention* and *Visibility of System Status*.

Navigation was improved for better intuitiveness: documentation was moved to a separate button, defect selection was made more intuitive, and an Undo button was introduced, supporting *User Control and Freedom*. Tutorials were simplified and redesigned as interactive playgrounds to improve retention.

Functional improvements included easier deselection of the Drag and Zoom tool, better statistical calculations, and automatic opening of the "Annotation" tab. Cosmetic fixes, such as feedback descriptions and font size adjustments, further refined the interface.

5.5 Deliver phase

Due to the limited availability of DE, the first step was conducting layman testing. The goal was to evaluate the core functionalities of the prototype and identify and fix fundamental usability issues. To make the PCD problem more understandable, we domain-transferred the annotation problem from PCD annotations into comprehensible

An actor	Mariana
A motivator	Ensuring correct cilia labeling
An action	Mariana selects the image she wants to review from the project. She inspects all existing annotations, including defect types and dynein arm labels, to confirm correctness. If a label is incorrect, Mariana updates it to accurate defect or dynein arms type. If a specific defect type is missing, she creates a new defect class. If Mariana identifies any unnecessary labels, she deletes them. Mariana creates new annotations for any cilia that have not yet been annotated, ensuring they are labeled correctly.
A resolution	After completing the review, Mariana confirms the accuracy of the annotations.

Table 3: User scenario 3: Mariana checks the correctness of the labeling of the cilia

tasks of cookie annotations that are understandable by a wide user audience. Participants had to label all the cookies in the picture, and for each cookie, they had to identify the flavor by the color of the annotation, representing a microtubular defect, and sprinkles of the cookie by the mark of the annotation, representing the dynein arms of the cilia.

8 participants were selected based on predefined user profiles to ensure diversity in age and technical skills, and they were not from the medical background. Participants completed 12 tasks focused on core functionalities such as editing annotations, class creation, and tool interactions. To assess retention and ease of use, participants annotated two images — one earlier in the session and one towards the end. Immediate feedback was gathered after each task, and a final questionnaire provided additional insights for improvement.

Performed tasks were as follows:

1. You've just launched the application and want to understand what it's all about.

2. The layout tutorial. Find out what features the application provides.

3. Upload images. Colleague sent you two cookie images which you have saved in the folder. Ensure these images are available in the app.

4. Annotate one cookie. You want to learn how to annotate images and try it on one cookie.

5. Annotate image. Your colleague needs a detailed analysis of the first image.

6. Change annotation. While reviewing your annotations, you realize one of the annotations is wrong.

7. Delete annotation. You've spotted an annotation in the wrong place.

8. New class. While analyzing the cookies, you realize some cookies do not represent the chosen flavor and the application doesn't provide it. You would need a new flavor for them.

9. Point size and Zoom. You need a closer look at one specific annotation to check its accuracy. Adjust its size and focus on it for a better view.

10. Whole diagnostic process. Your colleague needs you to review the second image. How many cookies are with chocolate sprinkles?

11. Documentation. You're trying to complete a task but aren't sure how a certain feature works. Figure out how to proceed.

12. Feedback. You've noticed something about the app that could be improved. Let the team know your thoughts to help them make it even better.

6 Evaluation and Discussion

The layman usability testing revealed several usability issues, and throughout the sessions, we collected metrics and participants' answers to interview and questionnaires.

6.1 Metrics

We collected metrics on task completion rate (Table 5), task time (Table 6), and error rate (Table 7) to evaluate performance. We calculated average (Avg) and standard deviation (Std). Most participants completed tasks successfully and errorless, except in Task 4 (difficulty adding a mark to annotation) and Task 9 (unclear instructions).

User responses highlighted initial struggles with annotation workflows, though participants found them intuitive once learned. Positive feedback emphasized satisfaction with the manual annotation process while recurring issues included difficulty finding functions (e.g., adding classes, adjusting point sizes) and overly dense tutorials. These insights underscore the need to improve feature discoverability and streamline onboarding.

6.2 Usability problems

We identified twelve usability problems. Participants found the **tutorials** overwhelming which was evident when they forgot how to add dynein arm markers. One participant **accidentally deleted an annotated image** twice, highlighting the need for a confirmation modal to improve heuristic *Error Prevention*. Users struggled with **Zoom and Drag** tool functionality and their deselection. Two participants searched for an **Undo button**, and all of

Deleting an image			
Severity	4 - Usability catastrophe	**Problem count**	1
Description	The participant accidentally deleted an annotated image.		
Solution	Add a modal window to confirm the removal of the image.		
Drag and zoom			
Severity	4 - Usability catastrophe	**Problem count**	3
Description	Participants found it difficult to unselect drag or zoom tool when they wanted to start annotating. They clicked the button multiple times in order to deselect it. They also did not know how to use drag and zoom.		
Solution	Fix the unselecting the tool by by clicking the button again. When zoom is selected, the ”Zoom with mouse wheel” tooltip will be displayed. When drag is selected, the ”Move by clicking and dragging the image” tooltip will be displayed.		
Counting statistics			
Severity	4 - Usability catastrophe	**Problem count**	3
Description	Counting statistics did not work in the layman’s version.		
Solution	Fix counting of statistics in layman’s version.		
Undo button			
Severity	3 - Major usability problem	**Problem count**	2
Description	Participants searched for the Undo button when they wanted to undo a step.		
Solution	Add an undo button to the navigation bar. Undo button will be able to revert 5 previous steps.		
Context menu			
Severity	3 - Major usability problem	**Problem count**	3
Description	The context menu is displayed below the selected image.		
Solution	Fix the context menu Z-index to display above the annotated image.		

Table 4: Top 5 problems of layman usability testing

Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10	Task 11	Task 12
100%	100%	100%	50%	100%	100%	100%	100%	67%	100%	100%	100%

Table 5: Task completion rates of performed tasks in layman usability testing

them instinctively looked for the **adding new defect class** in the class selection menu. Cosmetic issues included **misplaced context menus, small font sizes in graphs, and unclear feedback descriptions**. Participants also found **Documentation** unintuitive under Settings, suggesting a dedicated button. The **active tab in the right sidebar** was unclear, and the **statistical calculation** feature was non-functional in the simplified prototype. Lastly, a participant suggested an **annotation duplication feature**. This idea is worth discussing further with DE to determine its efficiency and usability. These issues were addressed in the third iteration (Section 5.4.3).

Table 4 lists TOP 5 usability issues. Each problem is rated based on severity using the following scale:

- 0 - I don’t agree this is a usability problem at all
- 1 - Cosmetic problem only, should be fixed only if extra time is available
- 2 - Minor usability problem
- 3 - Major usability problem, important to fix
- 4 - Usability catastrophe, needs to be fixed before the product can be released

7 Future work

In future work, we plan to test the prototype with DE and her two colleagues. Then, once the prototype is ready for manual annotation, we plan to enhance the prototype with the AI-assisted workflow to boost DE’s efficiency in their routine. We will ensure the tool mitigates risks associated with AI integration and provides clear, transparent explanations of AI outputs to build user’s trust. The prototype will be tested with DE using the Wizard of Oz method. Feedback from this testing will be incorporated to refine the prototype, making it ready for expert use.

	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10	Task 11	Task 12
Avg	54	124	18,7	309,3	316	53	5,7	81,7	131,7	274,3	17,7	18,3
Std	25,9	51,8	14,8	91,5	124,9	63,3	4	20,2	93	90,5	23,7	16,2

Table 6: Task completion time in seconds of performed tasks in layman usability testing

	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10	Task 11	Task 12
Avg	0	0	0,3	0	3,7	2	0	2,7	4	2,3	0	1
Std	0	0	0,6	0	6,4	2	0	1,5	3,6	3,2	0	1,7

Table 7: Error rate of performed tasks in layman usability testing

8 Conclusion

The goal of our research was to create a user interface supporting histopathologists in diagnosing PCD. Using our proposed design model DEDDM, the prototype was developed to meet the needs of DE with limited time. We applied the proposed methodology during a two-year-long case study with DE directly involved in PCD diagnostics. The proposed user interface for the PCD annotation tool provides the possibility of manual annotation of digitized specimens, including features such as tutorials, documentation, defect class creation and management, and statistical calculations.

The prototype was domain-transfered into a widely-understandable annotation problem for the layman usability testing which revealed 12 usability issues which were addressed in the third iteration. Participants reported no significant issues with task completion and found the application simple and enjoyable to use once they became familiar with its layout. However, they initially struggled with understanding how manual annotation worked, which was resolved by transforming the tutorial into an interactive playground.

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