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From the Classroom

Impact of image based artificial intelligence on workflow efficiency and diagnostic accuracy in clinical practice: a pathology-focused literature review

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Abstract

Histological diagnostics enable patient-specific therapy options. Given rising cancer incidence and a growing shortage of qualified personnel, implementing digital pathology workflows with AI integration appears to be a promising solution. This review assesses the literature on AI implementation in pathology regarding diagnostic accuracy, workflow efficiency, and documented challenges. Publications from January 2025 to February 2026 focusing on AI in histology and cytology were evaluated. From 318 identified studies, 16 articles were included after applying inclusion and quality criteria, comprising narrative reviews, pilot studies, validation and implementation studies. Included studies demonstrated high diagnostic accuracy and potential for improved workflow efficiency. Reduction of interobserver variability and standardization of biomarker testing were identified as key benefits. Open questions regarding validation, regulation, and ethics remain. AI-assisted pathology diagnostics shows promising potential regarding diagnostic quality, efficiency, and addressing current staffing challenges. Cost-effectiveness and regulatory aspects require further evaluation.

Key words

artificial intelligence, digital pathology, workflow efficiency, diagnostic accuracy, histology

Background

In recent years, artificial intelligence (AI) applications were introduced to the general population and quickly incorporated themselves in a diverse way in many parts of our lives. In many aspects it seems to make our lives easier. Especially using generative AI, specifically large language models for tasks like data extraction and analyses has optimised different workflows. Implementing a diverse set of artificial intelligence tools into the healthcare system, a world with high quality demands and often limited time and personnel resources, seems to be the next logical step. Algorithms could help to sort through medical records, retrieve and preprocess relevant information and aid clinicians to the right differential diagnosis as well as further diagnostics. Large language models (LLM) in the healthcare setting can also help to improve patient education, streamline or give aid to clinical practice or support medical education and training [1].

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Another even vaster field of application of artificial intelligence or algorithms seems to be medical image analysis. Using machine learning algorithms to specialise in image pattern recognition could help to make image diagnostics more precise or at least more efficient. Medical images play a huge role in many different parts of the healthcare system. Radiology comes to mind first when thinking about medical imaging, but other medical fields like pathology, dermatology, cardiology, gastroenterology or ophthalmology are based on analysing different kinds of images as well. Using algorithms could help to quickly screen large amounts of image data, distinguish between cases with positive or negative results and help to accelerate the diagnostic process and thus medical decision making.

In the last couple of years several AI applications are already in use or tested in the medical field. Different problems have arisen in the past, several of them still not fully solved. Initially regulatory affairs regarding data protection, were the main concern, especially when using AI algorithms in the healthcare system [2]. Several of these issues were addressed in the AI Act of the European Union (Regulation (EU) 2024/1689 of the European parliament and of the council, 2024). Other concerns with using artificial intelligence in the medical field like algorithm bias and problems which could arise with unsupervised use of trainees or patients remain mainly unsolved. Professional oversight of the use of AI tools in the healthcare system seems to be indispensable [1].

As mentioned before, the use of medical image analysis seems to show great potential for making medical workflows easier and more efficient as well as potentially more precise. Pathologists play a fundamental role in providing information for the care of patients especially in the field of oncology. This is routinely done via analysing human tissue under the microscope. Methods in the field of histology or cytology have not much changed since the 19th century. New techniques which were introduced to pathology practise in the last couple of decades were immunohistochemical testing and molecular diagnostics. These newer methods made the diagnostics more precise and thus enabled a targeted way of therapy for patients. The implementation of digital pathology which consists of scanning the slides of human tissue samples (whole slide imaging – WSI) has revolutionized the field of histology and cytology in the last couple of years. Advantages like remote access to patient cases can help to use personnel resources, which are hard to come by in the last couple of years, more effectively. Using digital pathology can also help to make measurements more accurate. Disadvantages or challenges which occur with digital pathology are the needed large long-term storage as well as high implementation cost [3].

As many new cancer targeted therapies are emerging over the last decade which make therapy options more diverse, the need for diagnostic testing in the field of pathology is increasing as well. Molecular as well as immunohistochemical testing are now part of standard diagnostics in many different cancer subtypes. These new and fascinating opportunities have made the workload in the field of pathology gradually more difficult. Additionally it is expected that the incidence of cancer will increase over the next decades [4], which indicates that diagnostic resources in the field of pathology will be very much needed. Many countries in Europe as well as USA and Canada suffer from an increasing shortage of qualified staff in the field of pathology as well as in many other medical areas for the last decade [5]. Reasons for pathology staff shortage are diverse and include a high proportion of pathologists over 55 years of age, increased workload demands, insufficient training of new pathologists as well as low attractiveness of this subspeciality as a consequence [6], [7]. As a speciality which is crucial for giving the diagnostic basis for further treatment planning, the mentioned worldwide human resource shortage is one of the causes of underuse of effective medical interventions and services in many countries and therefor influences directly the overall healthcare management [8].

Realizing a digital pathology workflow opens possibilities to use image diagnostic algorithms which could have a positive impact regarding the mentioned personnel difficulties. Using histology based diagnostic algorithms and small trained AI models for specific immunohistochemical testing in the setting of biomarker testing could at least in theory help to reduce the described increasing workload of pathologists and aid to prioritize cases and thus improve workflow efficiency and capacity of pathology laboratories. Secondary, other features like scan or staining quality control, triaging to improve workflow efficiency, monitoring of diagnostic results and standardised AI analysis of biomarkers could have a great influence on overall accuracy and quality in the diagnostic process. Challenges in implementing artificial intelligence tools into pathology institutes have been described as well. Cost of digital pathology equipment, data storage, legal considerations as well as considerations regarding a vendor neutral imaging software to be capable of incorporation a vast diversity of potentially costly AI tools are some of the potential hurdles to be considered. Questions which have to be answered are how and in which setting artificial intelligence should be used and how loosing expertise in doing so could be prevented [9].

Implementing an image-based AI workflow is time consuming and comes with quite high initial investment. Digital slide scanners must be bought to make AI algorithm usage even possible. But AI integration does not stop there. IT infrastructure as well as security must be addressed. Connecting the imaging software (IMS) to the laboratory information software (LIS) is one part, another part is thinking about possibilities of local or cloud-based AI solutions, which could influence the overall cost long term as well as make a difference on legal data safety aspects. Another important part is initial training of the pathologists how to use AI properly and safely [9].

As mentioned before staff shortage and increasing workload is a real-life problem in the field of pathology in many countries [6], [7]. If implementing image-based AI into the histology workflow could help to manage the increasing workload and therefor reallocate pathologists' resources to more complex case interpretation, it could be a significant step forward to ensure a stable and efficient overall healthcare management and would possibly justify the cost. However, challenges and general considerations should also be addressed as some studies describe the usage of artificial intelligence in image-based diagnostics as a double-edged sword which can help solving the issues resulting because of staff shortage on the one hand but could increase the staff shortage itself on the other hand. Some studies suggest that AI integration in the healthcare workflow could result in loosing skills or in the case of trainees never learning specific skills at all. Furthermore, AI integration could make the field of pathology as a medical speciality even less attractive as the presumption could arise that this diagnostic field will be dominated by artificial intelligence application in the future and will not be challenging anymore [10].

The integration of artificial intelligence in the field of pathology seems to prompt questions about the future role of pathologists and how and when to use AI in diagnostic processes. Some suggest using it as some sort of quality control of human based diagnostics, others suggest a direct implementation into the workflow with the possibility of automated reporting without human interaction. Vos et al describes in their research article which changes and training programs should be assessed and done to foster competencies related to this new technology and to educate about its potential as well as limitations and bias [11].

Given this competing promises and possible perils, this small-scale literature review tries to answer the question which benefits regarding workflow efficiency and diagnostic accuracy in using AI in histology-based diagnostics are described in the literature. It aims to inform decisions of stakeholders in healthcare to possibly allocate resources to the emerging field of AI use in pathology while addressing possible emerging problems in integrating this new and fascinating technology and which possible workforce and professional development challenges must be done.

Aim of the study

This project thesis intends to evaluate the literature of the last year (2025 – 2026) regarding the outcome of implementation of artificial intelligence (AI) based diagnostic assistance tools in the setting of clinical diagnostic healthcare. It aims to assess which impact it has on topics like workflow efficiency and diagnostic accuracy with regards to diagnostics in pathology based on whole slide digital imaging. In this context the project focuses on literature relating to histology and cytology. Other parts of the field of pathology like molecular diagnostics and microbiology are not included in this essay.

The goal of this small-scale literature review is to inform about the topic of implementation of AI based diagnostic tools, which outcomes should be expected and therefor help healthcare management planning. If the assessed literature indicates measurable improvements e.g. in diagnostic clinician workload, diagnostic accuracy and workflow efficiency it could guide healthcare management processes to decide to allocate more resources into the evaluation of implementation of such relatively new AI based diagnostic tools.

The literature review at hand tries to answer the following question:

- What are the reported effects of image based artificial intelligence (AI) implementation on workflow efficiency and diagnostic accuracy in pathology diagnostic practice?
- Which challenges are described in the literature?

Methods of the literature review

Defining the scope of the literature review:

A PICOC (**P**opulation, **I**ntervention, **C**omparison, **O**utcomes and **C**ontext) framework [12] was used and adapted to further define the scope of this literature review:

Table 1: PICOC framework

Population	Clinicians and healthcare workers involved in diagnostic workflows of medicine, particularly pathology. Patients whose diagnoses are affected by AI-assisted procedures.

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Intervention	Implementation of artificial intelligence based diagnostic tools or procedures within diagnostic workflows with focus on whole slide digital pathology in the field of histology and cytology
Comparison	Conventional diagnostic workflows without AI assistance – standard human based diagnostic interpretation
Outcome	Reported impact on workflow efficiency (e.g. task duration, interpretation time, workload) Reported impact on diagnostic accuracy (e.g. sensitivity, specificity, reduction in diagnostic errors)
Context	Clinical practice settings - including hospital-based pathology institutes with focus on implementation factors (staff experience, workflow integration and challenges)

Databases and search terms

To conduct the search PubMed® database was used. Keeping the predefined PICOC in mind specific search terms where identified.

Table 2: Search terms

Search term	Medical Subject Headings (MeSH) terms
Artificial intelligence	Artificial Intelligence; Intelligent Systems; Machine Learning; Deep Learning; Dimensionality Reduction; Ensemble Learning; Federated Learning; Reinforcement Machine Learning; Representation Machine Learning; Supervised Machine Learning; Transfer Machine Learning; Unsupervised Machine Learning; Particle Swarm Optimization; Pattern Analysis, Machine; Prediction Methods, Machine; Predictive Learning Models; Sentiment Analysis
Workflow efficiency	Efficiency, Organizational; Workflow
Diagnostic Accuracy	Sensitivity and Specificity; Diagnostic Accuracy
Pathology	Forensic Pathology; Neuropathology; Pathology, Clinical; Cytology; Pathology, Molecular; Pathology, Surgical; Telepathology

Search strategy

The search strategy of this limited literature review included an **initial scoping search** primarily to verify the relevance of the topic. Furthermore after reading several studies relevant to the topic the literature search terms, mentioned above, where developed. Subsequently these search terms were used to conduct three **main searches** on Pubmed®, including literature of the years January **2025** until February **2026.**

Table 3: Search term combinations

Search	Search term combinations (MESH terms are not listed)
#1	((artificial intelligence) AND (workflow efficiency)) AND (diagnostic accuracy)) AND (pathology)
#2	((artificial intelligence) AND (workflow efficiency)) AND (pathology)
#3	((artificial intelligence) AND (diagnostic accuracy)) AND (pathology)

The literature was screened via reading the title and abstract of each study and using predefined inclusion criteria (relevance to pathology, image based artificial intelligence, workflow efficiency and diagnostic accuracy) as well as categorizing the articles in four distinct categories regarding the relevance to the research question.

Table 4: Relevance categories

Categories regarding relevance	
Highly relevant	Directly Addresses Workflow Efficiency and/or Diagnostic Accuracy in Pathology
Relevant	Addresses AI in Pathology with Some Focus on Efficiency or Accuracy
Potentially relevant	Subspecialty-Focused
Less suitable	None of the above

In the last step, a **bibliography search** of the remaining topic relevant literature was done to identify possible relevant literature which was not found using the previously described search terms. Literature identified via the bibliography search was also matched against the mentioned inclusion criteria as well as categories.

Data synthesis and quality assessment

The documentation of the data collection as well as the synthesis was done via an Excel based form. Furthermore, quality assessment of the included literature was done using different criteria depending on the quantitative or qualitative nature of the articles.

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Table 5: Quality criteria part 1

Quality criteria for quantitative studies	
Reference	a comparison with a reference method was performed (reporting without AI assistance)
Method	the applied tests were sufficiently described (e.g. AI assistance software tools)
Power	there were enough samples analysed to support the conclusions (>10 samples)

Table 6: Quality criteria part 2

Quality criteria for qualitative studies	
Transparency	all important work steps are documented and traceable
Intersubjectivity	the subjective data obtained are discussed and critically reflected upon
Process documentation	it is clearly described how the literature was conducted

In a last step the key content as well as the following data were extracted if applicable: diagnostic accuracy, workflow efficiency, used AI and IMS, relevant limitations, key-content and challenges/ considerations. These different result data groups were used to form discussion points to simplify the data evaluation.

Disclaimer about AI usage

Artificial intelligence tools were used in the preparation of this thesis. ChatGPT (OpenAI) was used to assist with language editing. Open Evidence was used for the initial scoping literature review and in some parts for assessing the relevance of the literature. The author reviewed and verified all content and takes full responsibility for the final thesis.

Results

After conducting the three searches a profound amount of literature was found. Search number one and two with focus on “workflow efficiency” alone (221 articles) and in combination with “diagnostic accuracy” (127 articles) revealed partially overlapping literature (30 articles). Search number three with focus on “diagnostic accuracy” on the other hand showed an abundance of results (3,482 articles). As this amount of literature would go well beyond the scope of this limited literature review and as the main focus of this review relies more on workflow efficiency regarding the described increasing lack of personnel and healthcare management considerations, search number three was excluded.

The remaining literature of search number one and two (318 articles) was screened via reading the title and abstract of each study and using predefined inclusion. The remaining 42 articles

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were further included and sought for retrieval. Three articles could not be obtained as there was limited access. After categorizing the remaining 39 articles in four distinct categories regarding the relevance to the research question, only articles highly relevant to the topic where further included (15 articles). Further data synthesis as well as matching against quality criteria was done. After searching the bibliography of the included articles one additional article was found with high relevance to the topic. This article was included although its publication date (2024) was out of the predefined search span (January 2025 until February 2026).

The selected articles included narrative reviews (n=7), pilot studies (n=2), validation studies (n=2), implementation studies (n=2), one technical report (n=1), one comparative study (n=1) and one systematic review (n=1). Seven of the 16 articles could be classified as quantitative research; the remaining 9 studies are of qualitative research nature.

Discussion

Principal findings

Following the aim of the literature review at hand, sixteen articles were included which considered the usage of artificial intelligence in the setting of diagnostic procedures in the field of pathology. Most of these included articles were narrative reviews, but also some implementation studies as well as validation studies relevant to the topic were identified. Several topics re-echoed throughout most of the studies like the already mentioned assumed high accuracy of artificial intelligence and the possibility to reduce workload as well as interobserver variability. These topics as well as the reported challenges and considerations in using artificial intelligence will be commented in more detail in the following sections.

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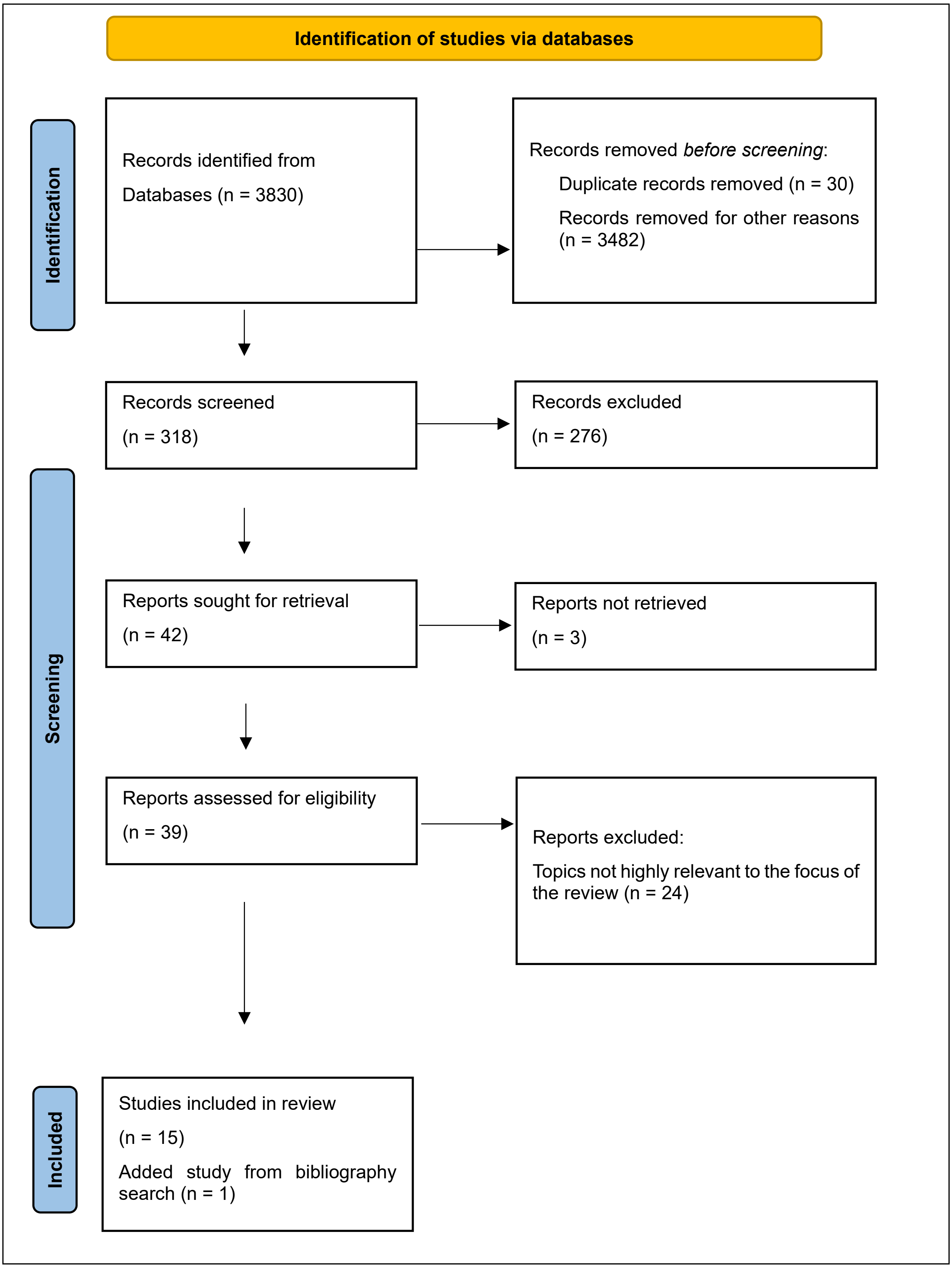
Figure 1: PRISMA 2020 flow diagram for new systematic reviews which included searches of databases



Diagnostic accuracy

The possibility of improvement of interobserver variability was mentioned in five out of the sixteen included articles [9], [13], [14], [15], [16]. Interobserver variability is a known problem in the field of pathology. Reason for this is the nature of histology which is an inherently interpretative diagnostic speciality. Although an abundance of diagnostic criteria, guidelines and WHO recommendations especially regarding tumour diagnostics do exist, morphologic features may be differently interpreted among pathologists. These differing interpretations are most pronounced in topics like grading of dysplasia, vascular or lymphovascular invasion, as well as in grey areas like differentiation between borderline malignant and malignant. Interobserver variability in pathology seems to be a significant issue as it can affect the immediate patient management [17], [18], [19]. The possibility to further standardize histology diagnosis via using artificial intelligence therefore seems to be very promising. Ivanov et al reviewed literature regarding the use of AI tools in the setting of breast cancer diagnostics. In this article it is not only mentioned that the histology diagnostic itself can be highly variable depending on the pathologist but also the biomarker interpretation. Breast cancer treatment is influenced by biomarkers like expression of oestrogen or progesterone receptor as well as HER2 receptor. Using artificial intelligence for this biomarker interpretation could at least provide consistent results. In their review they concluded that artificial intelligence could be of use in regards to interobserver variability and shows some promising results but as the usage of AI models is still evolving reliable data regarding this advantage is still missing [13]. Wu et al showed in their validation study of an AI tool for immunohistochemical evaluation as well as scoring of the proliferative activity of breast cancer with antibodies against PHH3 a good overall performance with high concordance with manual scores. It was possible to consistently reproduce scores as well as hotspot recognition. They discussed that the so called "ground truth", the reference for AI training can be a bias itself. Training slide annotation is an important part of AI model learning. Trying to find a consensus of multiple pathologists in the highly subjective field of proliferation score can result in a too restrictively trained AI model which would subsequently underscore the specimens [16].

Another important aspect of implementing AI in histology is the expected sensitivity and specificity, which several included articles addressed. In their systematic review and meta-analysis, McGenity et al (100 articles reviewed, 48 in the meta-analysis) found a mean sensitivity of 96,3% (CI 94.1-97.7) and specificity of 93,3% (CI 90.5-95.4), while noting heterogeneity in study design as limitation. Among the largest subsets (gastrointestinal, breast and urological pathology), gastrointestinal showed the highest mean sensitivity and breast the lowest, attributed to the AI training sets and the inherent difficulty of breast cancer histology [20]. Similarly, Ivanov et al reported an accuracy range of 75% to 95% across breast cancer histopathology applications [13].

Rienda et al evaluated a Pan Cancer AI tool for recognizing invasive cancer across 16 tissue types, achieving 90,3% accuracy, with 93,3% sensitivity and 87,5% specificity in biopsies and 94,7% sensitivity and 75,0% specificity in resections. They argued the lower specificity was acceptable given the tool's intended use for screening with human oversight [21]. In cervical cytology, Rivera Rolon et al validated AI on over 1400 slides, reaching 97% accuracy, 82% sensitivity and 99% specificity. They emphasized that a high negative predictive value is critical here, as false negatives carry severe patient implications, and likewise positioned AI as a screening aid with human oversight before reporting [22].

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Two articles addressed AI in prostate histological diagnostics. Grobholz et al concluded that AI tools showed high diagnostic accuracy in prostate cancer diagnosis, citing one study in which AI-supported pathologists improved sensitivity by 8% and specificity by 0,7% [23], [24]. Zhang et al reported a prostate biopsy AI model trained on more than 1700 whole slide images achieving 97% accuracy, 98% sensitivity and 96% specificity against the established ground truth [25].

In summary, the included studies show promising results regarding aspects of diagnostic accuracy like sensitivity as well as specificity and interobserver variability in the use of artificial intelligence in subspecialised fields like breast and prostate pathology as well as pan cancer models. Some studies mention that a higher sensitivity at the cost of a lower specificity can be accepted as the AI workflow is not meant to be used as a stand-alone solution but as a help for screening histology samples.

Workflow efficiency

Diagnostic accuracy, good results on sensitivity as well as specificity are important parts to consider when thinking about implementing artificial intelligence in diagnostics as it very much influences the safety of using this new technology. As mentioned, implementation of digital pathology as well as artificial intelligence tools usually comes with high implementation cost [9] evaluation how this technology can help in regards to workflow efficiency and hence be of use in times of personnel shortage and increasing demands in the field of oncology [5] seems to be crucial.

In the included studies automation of routine tasks is most frequently mentioned as an aspect which could influence workflow efficiency in the field of pathology [14], [15], [23], [26], [27]. But what does this really mean? Grobholz et al describe the potential use of AI in surgical pathology for automated triaging of cases [23]. In this aspect AI could be used to influence the workflow so that pathologists would have an AI pre-screened working list with different types of urgency categories attached to the different cases. Brodsky et al. mention in their article that this automated triage of pre-screened whole slide histology-images could also be used to distribute the cases automatically among the pathologists with metrics in mind like best use of personnel capacities as well as different specialization grade [26]. In their review they report a study of Mayall et al which tested an AI based classifier for triaging large bowel biopsies into several categories regarding their neoplastic or inflammatory nature and subsequently were able to improve turnaround times significantly [28]. The same study group reported another interesting possible application of AI utilization in the field of pathology, which is not image based but could very much influence workflow efficiency and allocate resources of pathologists to more important tasks. In their recent study they describe the application of artificial intelligence language processing and machine learning tools for automated extraction of diagnostic information from histology reports to quickly and accurately form so called SNOMED coding (Systematized NOmenclature of MEDicine coding). This coding system is used to make narrative pathology reports readable throughout different systems and hence enable different data analytics for various kinds of registries, science purposes or quality aspects. Manually coding is time consuming as well as potentially subjective. In their study Mayall et al showed that using AI for this purpose outperforms human coding in speed and accuracy [29].

Chong et al classified the use of AI in pathology in three different types which alters how or in which way this tool can influence workflow efficiency. These three categories of intended use are quality control, AI-assisted screening and AI-based primary screening. They describe these three different applications with regards to their use in cytopathology. Using AI as a quality control tool would mean to retrospectively analyse image-slides of reports which are already finalized by pathologists. In this setting it would not so much influence the workflow efficiency itself rather than act as a safety net to recognize potential discrepancies. AI-assisted screening on the other hand would imply more influence of artificial intelligence in the reporting itself. This setting can be done in cytopathology where usually a cytotechnologist screens the slides, and a pathologist does a second review. AI could be used as a supervisory control after the first step of screening via a cytotechnologist. If the reported finding of the cytotechnologist is concordant with the suggested classification of the used AI tool a direct report could be done, skipping the time consuming second review via a pathologist. The third application of AI mentioned in the review would be AI-based primary screening. In this setting AI tools are used for screening and negative cases would be signed out without human interaction. In this scenario high level of AI integration would have to be done as well as extensive validation to ensure patient safety [30].

In the reviewed literature other possible aspects of AI use in pathology with effects on workflow efficiency are mentioned as well. Many of the included articles discuss the influence of AI tools on immunohistochemistry use [9], [31], [32], [33]. Immunohistochemistry in the field of histology is used for different purposes like classifying the origin of a metastases or to test for specific biomarkers which would enable targeted therapy. Its use is associated with increased expenditure of work as well as personnel and technical expenses. Deman et al described the use of AI as a pre-screening tool in prostate biopsies. They reported that immunohistochemical testing could be decreased by one third. The application of AI as a pre-screening tool seemed to help in challenging cases and give the pathologists more confidence in their primary diagnosis and thus reduce diagnostic uncertainty and the use of immunohistochemistry [9]. Blilie et al as well as Eloy et al reported quite similar results in their studies which also described the use of AI in the field of prostate biopsies. In their studies the use of immunohistochemistry decreased by up to 80,6% [31] as well as 20% [32]. Flach et al used a different application of artificial intelligence in histology and tested two different AI tools for detecting lymph node metastases of different kind of solid tumours. Searching for lymph node metastases is a time consuming and tedious process for pathologists. Depending on the workload as well as training status immunohistochemistry is frequently used by pathologists to make this task easier. In their study the use of AI screening for lymph node metastases showed good sensitivity and could thus help in the diagnostic process of pathologists to decrease uncertainty, consecutively the use of immunohistochemistry as well as overall expenses [33].

Another important advantage of AI application with influence on the overall workflow efficiency it the reduction in turnaround time or reading time per case which also has a great influence on timely patient care. Several of the included studies reported positive results in this aspect [9], [14], [16], [22], [30], [33], [34]. To highlight some of them, Wu et al reported in their study about use of an AI tool in the automatic mitosis scoring in breast cancer a time reduction for the interpretation from 452 to 53 seconds per case [16]. Deman et al described a reduction in overall turnaround time in prostate biopsies of about 9 hours [9]. Eloy et al even reported that a faster reporting time by 24 hours could be achieved which possibly reduces time until surgery in prostate cancer cases [32].

Brodsky mentioned that another application of AI in pathology with influence on overall workflow efficiency and allocation of personnel resources is the use of AI tools in general quality control in histology. Tedious work like controlling staining quality or quality of the

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whole slide imaging which can be influenced by artifacts or focus issues for example, can be automated and hence free human resources for more challenging work [26].

Marra et al reported in their ESMO (European Society for Medical Oncology) associated review the influence of AI in the field of biomarker testing. As mentioned before evaluation of immunohistochemical biomarkers is time consuming and can be biased by interobserver variability. In reviewing 143 studies associated with AI for biomarker testing Marra et al recognized that the use of AI in this type of work can reduce the overall workload of pathologists [14].

Implementation challenges and considerations

The included 16 articles reported various challenges as well as considerations which should be done when implementing artificial intelligence in the field of pathology. These aspects can be structured into the following categories which will be discussed in the further sections: technical/ infrastructure challenges, data and validation challenges, regulatory and ethical considerations as well as workflow integration and human factors.

Technical and infrastructure challenges. Many of the included articles discuss the topic of high upfront implementation cost as a main initial challenge. Artificial intelligence use in clinical pathology is only possible if a digital pathology workflow is already in place. To establish this workflow a whole slide imaging scanner must be bought, IT infrastructure must be adequately organized as well as training of the personnel especially the technicians who will operate the system must be provided. These aspects are associated with high upfront cost [9], [14], [27], [30], [33]. Compatibility of the Imaging system (IMS) with the pre-existing Laboratory Information System (LIS) is also a very important part to be considered [9]. Data storage aspects must also be considered especially in the context of cloud storage use connected with the use of commercially available AI tools [15]. Scanning quality is another important and potentially limiting technical factor for AI implementation [30].

Data and validation challenges. Using artificial intelligence in the context of clinical diagnostics requires per European regulations AI tools with Confromite Europeene In Vitro Diagnostics (CE-IVD) certification which are hard to come by. These CE-IVD certified AI tools are often limited to specific manufacturer tested and validated applications which can make their use and hence their resulting advantages in clinical practice limited. Flach et al discussed in their comparative study this issue and how it results in the need of extensive validation studies which must be done by the laboratory and are cost and time extensive [33]. Additionally, well annotated, high-quality test data sets are needed to accomplish these validation studies. As the application of AI in diagnostic routine use is relatively new, these sets are also not easy to be found. Many of the included articles discuss this issue as well as further implications [13], [14], [15], [20], [23], [30], [31]. Dependent on the quality of these training data sets potential risk of bias or weak robustness of the AI model can be observed [20]. Well annotated histology sets need a reliable so called ground truth, which can be difficult to be defined especially with the already mentioned problem of interobserver-variability in the field of histology [30]. Another aspect to be considered are general AI bias problems in image-based diagnostics. Marra et al highlighted in their review the potential risk of “overfitting classifiers” when AI models are trained on restrictive data sets and do not include the right amount of diversity needed [14].

Regulatory and ethical considerations. Several of the included studies discuss topics of lack of standardized guidelines of implementation of AI in pathology, regulatory aspects like data privacy concerns as well as ethical considerations like equity and AI bias associated exclusion of rare or subpopulation specific traits [9], [13], [14], [15], [26], [27]. As mentioned above, extensive validation especially if AI is planned to be installed outside of its intended use but also in the setting of commercially available systems is needed. Specific guidelines how to do so are currently not available [33].

Workflow integration and human factors. In integrating artificial intelligence into the histology workflow human associated factors should be addressed. Several studies mention that initial staff training for the correct use of artificial intelligence is necessary to prevent or reduce the risk of over-reliance on AI and to promote acceptance of this new technology [9], [14], [20], [26]. Some of the included studies point out that at least at the current stage of implementation, AI in the context of pathology must be used as additional diagnostic tool rather than replacement of human expert labour [15], [21], [31].

Conclusion

The reviewed literature on AI implementation in pathology highlights promising benefits, including reduced interobserver variability, improved diagnostic accuracy and enhanced workflow efficiency. Integrating digital pathology with AI tools therefore appears to be a viable response to the pressing challenges of staff shortages and rising workloads in the field [6], [7]. However, several obstacles remain, including unresolved regulatory questions, a lack of established guidelines and high implementation costs that may restrict access to this technology [9], [30], [33].

This small-scale review has notable limitations. It included only literature published between 2025 and February 2026 and focused exclusively on AI applications in histology and cytology; other areas such as microbiology and molecular pathology were not considered and warrant further investigation. Due to the limited scope, search query three on AI and diagnostic accuracy was also excluded. An aspect that, given its central importance in medical diagnostics, should be examined in greater depth in future work. Furthermore, since high implementation costs appear to be a key barrier from a healthcare management perspective, a dedicated review on cost-effectiveness would be valuable.

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