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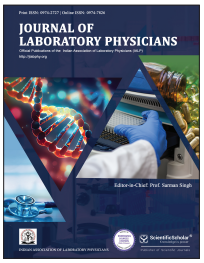

Original Article

A cross-sectional study on benefits, barriers, and adoption factors of artificial intelligence in the clinical laboratory

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ABSTRACT

Objectives: The objective of this study was to systematically assess laboratory medical professionals' perceptions of artificial intelligence (AI).

Materials and Methods: This exploratory cross-sectional study examines the opportunities, risks, and acceptance factors of AI from the perspective of laboratory medical professionals. The survey was based on standardized Likert scale questionnaires, including analytic hierarchy process (AHP) analyses.

Statistical analysis: Likert scales were numerically coded, and dichotomous variables were recorded as binary values. Decisions were weighted using Saaty's AHP, including consistency checks (consistency ratio <0.1), supplemented by descriptive statistics and non-parametric tests (Wilcoxon signed-rank test, $\alpha = 0.05$).

Results: The quantitative analysis showed a low level of previous experience with AI, but a predominantly positive attitude: AI was perceived significantly more often as an opportunity than as a risk (mean 4.22 vs. mean 2.5) ($p < 0.001$). Participants with <20 years of professional experience consistently rated positive aspects (e.g., quality improvement and reduced workload) higher than their more experienced colleagues. An AHP opportunity analysis identified time savings as the most important benefit, followed by improved diagnostic quality and reduced workload. In the AHP risk analysis, professional uncertainty was prioritized ahead of liability issues and technological dependence.

Conclusion: Laboratory medical professionals see AI primarily as an opportunity. In addition to technological requirements and foreseeable clinical benefits, legal and ethical framework conditions and employee acceptance must also be taken into account as a further dimension to drive forward AI implementations.

Keywords: Artificial intelligence, Diagnostic workflow, Laboratory automation, Laboratory personnel

INTRODUCTION

Artificial intelligence (AI) is becoming increasingly widespread in healthcare. The profound changes encompass administrative and organizational processes and also affect clinical operations. Numerous studies have investigated the clinical benefits of AI, but the perspectives of laboratory medical professionals have been little researched to date. Previous research has shown that AI-supported systems in laboratory medicine can enable process optimization, quality improvements, and time savings, among other things.[1,2] There is no single overarching definition of AI, but generally speaking, AI refers to systems that mimic human intelligence.

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Medical laboratories naturally generate large amounts of data. These large amounts of data correspond to big data, as they are extensive, fast, complex, and structured in different ways. Machine learning applications are primarily used in laboratory medical settings, as they can recognize patterns in large amounts of data and derive rules from them. Machine learning is used in laboratory medicine, particularly to predict the probability of disease or the results of other laboratory parameters.[3] However, AI not only offers options for optimizing core medical processes, i.e., diagnostic processes in medical laboratories, but can also be used to improve health information management. There is great potential in medical coding and the management and processing of data. AI-supported data management is primarily concerned with professional data quality, governance structures, and data protection standards.[4] Electronic hospital information systems, such as patient display systems, laboratory information systems, and radiology information systems, have an extremely high usage rate and good functionality, and support clinical decision-making and workflows in daily hospital routines.[5] AI can be used to further improve the data management of such systems and implement better networking and aggregation between information systems.[4,5] Ethical implications must also be considered in the context of AI. Among other things, AI could exacerbate social inequality, as it can enable participation in less technologically advanced regions. The labor market must also train employees for the new realities of AI use through upskilling initiatives. Strategic data governance, which controls the ethical and responsible handling of data, was reported to be particularly important.[6] In the case of AI, regulation is necessary to reconcile human trust with potential innovations. The regulatory challenges are correspondingly complex and include agendas relating to data protection, the establishment of quality standards, global harmonization, and also reimbursability. This requires long-term government support programs and targeted training for staff at the national level, as well as international coordination to achieve robust standards.[7] Legal concerns are commonly accompanied by ethical concerns in the field of medicine. There is an urgent need for not only clear guidelines on the responsibility of doctors when using AI but also for the protection of patient rights, which includes the right to a human second opinion.[8] AI can thus be used to improve diagnostic accuracy, reduce errors, and implement real-time risk warnings and outcome predictions. Machine learning is suitable for processing superficially structured data (e.g., laboratory data and genetic data), while natural language processing is suitable for processing text-based requirements. Therefore, there is no universal AI for all areas of healthcare, and different ethical principles are consequently needed.[9]

The technology acceptance model (TAM) was introduced by Fred Davis in 1989 and is based on two fundamental constructs. The first is perceived usefulness, which in the TAM system reflects the extent to which a user believes that a system can reduce their workload. Second, TAM takes into account perceived ease of use, which indicates how effortless a system is to use. Technological innovations, particularly in the field of information and communication technology, have great potential to improve patient safety in healthcare, professionalize processes, make them more efficient, and reduce costs. Although technological progress in healthcare is advancing rapidly, individual and non-technical factors, such as the acceptance of new technologies in the healthcare sector, which is addressed by TAM, are also important success factors.[10,11] Rogers' diffusion theory examines the diffusion of innovations and thus offers a concept of how technologies spread within social systems. An essential attribute of the adoption rate is the relative advantage, which represents the benefits of the innovation over existing systems. Perception is also determined by compatibility with existing values and needs (compatibility) and the difficulty of use (complexity). Finally, the course and speed of adoption are also influenced by observability. This means that the more visible an innovation is in the social environment, the higher the probability that other people will become aware of it, discuss it, and ultimately adopt it themselves.[12]

MATERIALS AND METHODS

Objective

AI is already widely used in medicine, and further AI establishments and implementations are unstoppable and set the tone for medical progress. When it comes to technological revolutions, people's perspectives should also be taken into account. On the one hand, technical developments (including digital ones) should improve people's quality of life, *per se*. On the other hand, technological developments are adapted more quickly and in a more targeted manner when they are accepted by the actors involved. In addition to the formal requirements for successful AI implementation in medicine, scientific work very often also takes the human factor into account. This research content strongly reflects the general public's perception of AI in healthcare.[13] Patient-centered medicine must remain the highest maxim of modern medicine, especially in times of technological change, when corporate interests can gain disproportionate weight. To continue to pursue rapid and, above all, technological AI-focused change in healthcare, stakeholders in the healthcare sector are called upon to act. They are currently still part of the system and thus set the pace for socially sustainable implementation. In addition to the innovation component (=AI), people play a key role in dissemination. Acceptance of the new AI methods by healthcare professionals accelerates internal implementation and can also convince other sections

of the population in terms of shaping public opinion (patient contact).

Aim of the study

The aim of the study was to record the views of laboratory medical professionals on AI. A systematic analysis was therefore carried out to determine whether AI is perceived as an opportunity or a risk by laboratory medical staff in their everyday work.

Study design and setting

A questionnaire survey was conducted, with participation being voluntary, anonymous, and subject to written informed consent. Fifty-five employees were recruited from the Institute for Medical and Chemical Laboratory Diagnostics, Wels-Grieskirchen Hospital, Wels, Austria. The questionnaire contained only closed questions. When creating the questionnaires, care was taken to ensure that the contents of Rogers' diffusion theory and Davis' TAM were reflected, thereby enabling a targeted operationalization of the collected data based on these established models. Key elements of TAM, such as perceived usefulness, are represented by questions about the improved quality achieved not only through AI in medical laboratories but also through the reduction in workload. Perceived ease of use was derived from a specific question about the simplicity of using AI. This question simultaneously addresses three relevant features of Rogers' diffusion theory: Perceived relative usefulness, assessment of the degree of difficulty in using AI systems (complexity), and compatibility as an expression of the alignment of AI with existing working methods. Trialability was covered by specific questions about the level of experience of the employees at the beginning of the questionnaire and the interviews. A classic feature of Rogers' diffusion theory, the observability of results, could only be assessed to a limited extent in this study, as the participants' experience with the use of AI was very limited. In addition to the Likert questionnaire analysis, an analytic hierarchy process (AHP) analysis was performed. In this master's thesis, an AHP sub-analysis was performed to evaluate the opportunities offered by AI. The predefined criteria were time savings through AI, improved quality, and reduction of repetitive tasks. A further AHP sub-analysis for the evaluation of risks of AI in medical laboratories reflected the criteria of job insecurity/job loss, technological dependencies/loss of competence, and unclear liability issues. These criteria were structured hierarchically and compared in pairs. Approval by the Institutional Review Board was not required because no patient data were collected or analyzed. The study was conducted in accordance with the Declaration of Helsinki and its later amendments. All participants provided written informed consent.

Statistical analysis

A five-point Likert scale was used for scoring, with the categories 1 = strongly disagree, 2 = somewhat disagree, 3 = neutral, 4 = somewhat agree, and 5 = strongly agree. For statistical analysis, all scale values were numerically coded (1–5), while dichotomous questions (e.g., on previous AI use) were coded binarily (0 = no, 1 = yes). The AHP method, according to Saaty, enabled a hierarchical assessment of decisions and also pairwise comparisons of characteristics. In AHP, criteria are defined and then evaluated on a scale (1–9). Based on these criteria, an AHP comparison matrix was then created, structured in such a way that each evaluation contained an automatic reversal for the corresponding counterpart. Vectors were calculated using the pairwise criterion comparisons. The ratings in the comparison matrix were first normalized, and then, the average of each row was calculated, making the weightings traceable. Following the AHP analysis, a consistency assessment was carried out to check the consistency of the pairwise comparisons. To do this, the largest eigenvalue was first estimated by multiplying the comparison matrix by the priority vector λ_{max}, and the consistency index (CI) was calculated using the formula [CI = λ_{max}−n/n−1] and compared to the random index (RI) tabulated for the respective matrix size to obtain the consistency ratio CR=CI/RI. Based on typical AHP metrics in medical studies, a value of <0.1 was classified as acceptable.[14,15]

The quantitative data were statistically evaluated using descriptive statistics and appropriate graphical representations (bar charts and pie charts). For inductive statistical calculations, no preliminary testing for normal distribution was carried out, as the Likert questionnaire surveys corresponded to ordinal-scaled evaluations and the calculations could be performed using the non-parametric Wilcoxon signed-rank test for paired samples. The statistical significance level was set at $\alpha = 0.05$. Incomplete questionnaires corresponded to a predefined exclusion criterion and were therefore not included in the evaluation. All calculations were performed using the Excel add-in "Analyse-IT®."

RESULTS

The basic demographic surveys showed a female predominance in the study population, with 48 females (87%) and seven males (13%) participants. The analysis of professional experience showed a largely balanced ratio. Twenty-eight laboratory professionals reported more than 20 years of professional experience, while 27 reported <20 years (51% vs. 49%).

The lowest value was 1.8 in the area of previous experience with AI. With values ranging from 3.24 to 3.93, it was found that many participants tend to see AI in laboratory operations as reducing workloads and improving quality, and that AI is predominantly associated with ease of use.

However, restrictive tendencies due to unresolved liability issues and ethical concerns could also be inferred from the data. A low value deviating from the neutral standpoint (2.75) was found for the question used to determine whether AI stands for high complexity and low traceability. A head-to-head comparison of the main questions showed that, in the perception of laboratory staff, AI is seen more as an opportunity than as a threat (4.22 vs. 2.51). In the inferential statistical analysis, this difference was found to be significant with $p < 0.001$. The data for the Likert scale analysis (comparison of opportunity and risk, questions 8 and 9) have been summarized in Figure 1 and Table 1.

In addition, an analysis of the results was carried out in a group comparison based on professional experience, as comparable group sizes were found in the basic data analysis. This shows a more pessimistic attitude toward AI in the group with >20 years of professional experience, with higher values for risk and lower values for opportunity compared with participants with <20 years of professional experience. The data on the group comparison based on professional experience have been shown in Figure 2 and Table 2.

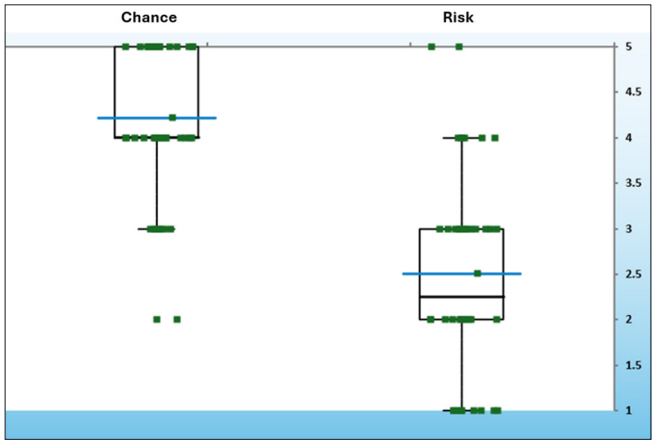

Figure 1: Comparison of opportunity and risk: Opportunity mean 4.22 versus risk mean 2.51; $p < 0.001$.



Figure 2: Presentation of the results on artificial intelligence perception in relation to professional experience.

The AHP analysis initially examined the opportunities offered by AI in the laboratory sector. This analysis showed that 55% of participants considered time savings to be more important than diagnostic quality and improved work quality (= reduction of repetitive tasks). The AHP analysis of AI risks in medical laboratories showed that job insecurity (job uncertainty) was rated as the most serious risk at 65%, followed by the impact of errors and unresolved liability issues at 19% and technological uncertainty and loss of competence at 16%. The consistency check of the AHP opportunity analysis yielded a consistency ratio of CR = 0.014 (λ e max = 3.016 and CL = 0.008), and the AHP risk analysis yielded a consistency calculation of CR = 0.096 (λ e max = 3.111, CI = 0.055). This means that the consistency ratio is below the standard threshold value of 0.10. Table 3 illustrates the results of the AHP analysis.

DISCUSSION

The use of AI also has positive effects in laboratory medicine. The potential for time savings through AI is

Table 1: Results of the Likert questionnaire surveys.

Likert survey	Mean score
Prior experience	1.8011
Reduction of workload	3.7438
Quality	3.9267
Ease of use	3.2516
Liability	3.2362
Ethics	3.7671
Complexity	2.7424
Opportunity (Chance)	4.2173
Risk	2.5087

Table 2: Overview of artificial intelligence perception among medical laboratory employees with varying degrees of professional experience.

Question	< 20 years of professional experience	> 20 years of professional experience
Prior experience	1.74	1.86
Reduction of workload	3.81	3.68
Quality	4.11	3.75
Ease of use	3.44	3.07
Liability	2.89	3.57
Ethics	3.93	3.61
Complexity	2.33	3.14
Opportunity (Chance)	4.37	4.07
Risk	2.3	2.71

Table 3: Opportunity and risk evaluation and weighting using the Analytic Hierarchy Process.

Opportunities			
Comparison matrix (Means)	**TS**	**Q**	**RRT**
TS (time savings)	1	2.45	3.4
Q (quality improvement)	0.41	1	4.31
RRT (reduction of repetitive tasks)	0.29	0.23	1
Normalized matrix	**TS**	**Q**	**RRT**
TS	0.59	0.67	0.39
Q	0.24	0.27	0.49
RRT	0.17	0.06	0.11
Priority vector (Opportunities)	**Weight**	**%**	
TS	0.55	55%	–
Q	0.34	34%	–
RRT	0.12	12%	–
Risks			
Comparison matrix (Means)	**JE**	**TD**	**LU**
JE (Job insecurity)	1	28	1.84
TD (Technological dependency)	0.04	1	2.02
LU (Liability uncertainty)	0.54	0.5	1
Normalized matrix	**JE**	**TD**	**LU**
JE	0.63	0.95	0.38
TD	0.02	0.03	0.42
LU	0.34	0.02	0.21
Priority vector (Risks)	**Weight**	**%**	
JE	0.65	65%	–
LU	0.19	19%	–
TD	0.16	16%	–

often demonstrated, especially in cytological microscopy assessments, where digital morphology with AI pre-classification can achieve significant time savings for employees.[16] AI also offers the potential to improve the diagnostic quality of medical laboratory analyses. In the automatic classification of urine sediment images, AI has already shown good results with high precision, among other things. This can help to avoid errors and improve standardization in medical laboratories, as manual sediment assessment is also subject to inter-rater variability.[17] In addition to improving quality and saving time, studies have also shown that AI can reduce turnaround times and repetitive tasks.[18] Previous studies investigated public perception of AI in the healthcare sector. In general, the public showed a certain degree of openness toward AI in healthcare. Trust in AI improved when decision-making processes were transparent, human oversight of AI could be ensured, and when people had already had their own experiences with relevant AI technologies.[19] At the beginning of this questionnaire survey, the study participants, i.e., laboratory staff, were asked about their previous level of experience with AI. The analysis of the questionnaires showed that the lowest mean value on the Likert scale was achieved in the area of previous experience and AI, meaning that the greatest deviation was recorded in this area and that the level of experience could generally be classified as low. A Europe-wide study examining the use of AI in medical laboratories revealed low AI utilization among the participating organizations. The majority (71.8%) of the institutions reported in the questionnaire study that they had no active AI projects running, and those laboratories with AI applications were predominantly tertiary hospitals (e.g., university hospitals). Gross deficiencies in the existing digital infrastructure were reported as a major hurdle; 25.1% of laboratories did not have Wi-Fi, five laboratories had no internet connection, 88.7% had limited or no access to third-party software, and 51.3% did not use cloud services. In addition to digital barriers, other problem areas mentioned included limited access to clinical data and a lack of AI knowledge.[20]

The question on improving quality through AI received the highest approval rating (apart from the main question on opportunity vs. risk and AI) with a mean value of 3.93 on the Likert scale. AI can improve quality in laboratory medicine, among other things, by reducing or even completely eliminating errors. According to Dodig *et al.*[21] there are various indications that point to improved quality through the use of AI in the laboratory. The authors also mention the opportunities for error reduction as a key factor. Standardized and reproducible processes allow results to be delivered faster and of better quality.[21] A clear trend emerged when comparing experience groups. Participants with <20 years of professional experience consistently scored higher on questions with positive connotations (reduction in workload, increased quality through AI, ease of use of AI, ethical compatibility, and AI as an opportunity) than participants with >20 years of professional experience. In contrast, the average Likert questionnaire scores for questions with negative connotations (unclear liability, high complexity, and AI as a risk) were consistently higher in the more experienced professional group. There are comparable confirmatory studies from other disciplines that similarly found an age gradient in attitudes toward AI and confirm that representatives of the younger generation are more open to AI, use AI more frequently, and also rate AI more positively.[22] In light of the adaptation factors, the relative advantage (or perceived use) was covered by questions about reducing workload, improving diagnostic quality, and ease of use (or perceived ease of use). Compatibility is demonstrated by asking about compatibility with ethical values. Complexity and observability are specifically addressed by the question, "AI applications are too complex and difficult

to understand." Observability was mapped using a question about AI experiences in the participants' own professional environment.[10-12] The analysis showed that the relative advantage is predominantly seen by participants with average Likert values of 3.75–3.93, as is compatibility (average value 3.76). The assumption that AI is too complex and difficult to understand (average value 2.75) tended to be rated as neutral or rejected. Overall, the analysis of these metrics shows that a positive attitude toward AI adoption prevails among participants at the laboratory. One exception to this is the opportunity for every staff member to try it out. The use of AI in the workplace was rated very low. This work showed that the penetration of AI is currently still very low and limited to a few sub-areas (e.g., Next Generation Sequencing) of the medical laboratory institute. Improvements could be achieved in this context through targeted rotations of employees from non-AI-related jobs to AI-supported activities. Depending on the time resources available, additional internships within the departments could provide further positive impetus. This study showed how the attitudes of laboratory medical staff toward AI can be systematically recorded. However, it should be critically noted that there are other dimensions besides the acceptance of laboratory staff. Laboratory-specific hurdles must also be considered, such as the integration of AI into laboratory information systems and middleware structures, clearly defined responsibilities in terms of quality assurance, and targeted training of staff.

CONCLUSIONS

Innovative enhancements, such as the use of AI, require technological progress. However, successful implementation also requires viable solutions for laboratory medical staff. This study demonstrated how such surveys can be conducted in a targeted manner in the laboratory medical environment. This single-center survey showed that AI is perceived as highly useful and moderately user-friendly, which represents a favorable starting point for future implementations.

Author's contributions: BS: Conceived and designed the study, developed the methodology, collected and analyzed the data, performed the statistical analyses, interpreted the results, and drafted and revised the manuscript; SGM: Critically reviewed the manuscript, provided intellectual input and comments, and contributed to manuscript revision. All authors read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Ethical approval: Institutional Review Board approval is not required, as this was an anonymous, non-interventional sociological survey among healthcare professionals..

Declaration of patient consent: The authors certify that they have obtained all appropriate participants' consent.

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Conflicts of interest: There are no conflicts of interest.

Use of artificial intelligence (AI)-assisted technology for manuscript preparation: The authors confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript and no images were manipulated using AI.

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