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Assessing Barriers and Benefits of Adoption of AI-Powered Cloud Storage in Clinical Laboratories Across Nepal, Bhutan, and India

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Abstract

Background

AI-integrated cloud computing system modernizes clinical labs by overcoming paper-based system limitations. Cloud systems offer efficiency, scalability, and real time data access, improving healthcare quality, system strength and regulatory frameworks for patient data security and cyber security risk mitigation. However, limited AI training scattered or fragmented data, tight cost control, and inadequate hardware or software creates a barrier for AI-based cloud system integration.

Objective

The objective of the studies is to evaluate the method of data storage, access, and data usage practices done currently in the labs. The study evaluates the effectiveness of AI integrated system together with the various effects of its implementation. The study also you value the expectation gap.

Methods

A retrospective survey of 113 participants conducted using a structured questionnaire. Key domains included comfort with LIS system, comfort with paper-based system, a viability of hardware and software, their adequacy, availability of Wi-Fi and the prospective of the survey takers on AI and modern technology.

Results

Most of the users were found to have transit from paper-based system to electronic Laboratory Information System. Though their satisfaction was rated moderately, there was a positive attitude towards AI with 71.7% showing familiarity with AI system. Statistically significant association was found between Wi-Fi quality and software satisfaction ($\chi 2 = 89.778$, $p < 0.001$). t-test showed noticeable expectation gap between current and desired states ($p = 0.0039$).

Conclusion

Enthought there is availability of resources it should be strategically implemented with appropriate Investments. AI has the potential to significantly enhance diagnostic accuracy, workflow efficiency, and overall healthcare outcomes. Though there are limitations, there is a positive perception and growing interest in artificial intelligence among laboratory workers. However, breaches like technical expertise and infrastructure are critical areas to investigate prior implementation.

Introduction

1.1 Problem Statement

Artificial Intelligence integrated Cloud computing has modernized and transformed clinical laboratories [1, 2]. Since paper-based system contained lots of limitations such as data fragmentation, slow and inefficient data retrieval, physical space inefficiencies, risk of errors, migration to cloud-based system has been accelerated [6]. Cloud based systems promise working efficiency, scalability, and real-time data accessibility, improving health care quality provided [4]. WHO also emphasizes that all data needs to be processed, stored and shared ethically and securely to manage breaches and to protect individuals' identity [5, 6]. AI powered Cloud Systems have strong regulatory frameworks for enhanced data security for protection of patient information and mitigate cybersecurity risk. In recent years healthcare services including laboratory diagnostic services, clinical documentation, prescription, etc.- have undergone digitalization [4]. Though unification of data was a challenge AI driven cloud system organization the data in a chronological view that patient's history and the unstructured health data is structured to completely understand the full picture [4, 8]. This has helped to provide better clinical decisions and helped improve decision-making for patients and caregivers [4].

"What works Globally doesn't expand globally" as mentioned in article by World Economic Forum shows the disparity between digital health implementation of high-income and developing nations [9]. In developing countries such as Bhutan, Nepal and India adoption of AI-integrated cloud-based system in clinical laboratory still faces challenges due to multiple structural and systemic challenges. This includes scattered or soil data, stagnant regulation, limited availability of AI training, fragmented marketing, data privacy concerns, burnt-out clinical staff, tight cost control, growing cyber threat, etc. [8].

Operational efficiency is highly compromised because of complex tools which complicate the work. This often happens when workers are not provided with enough training or due to incorporation of complex digital tools not optimally designed for local infrastructure; basically, such tools demand strong processors and high workforce capacity machinery [6, 7]. Therefore, instead of making the workflow more streamlined and smoother, this poorly integrated system can in turn complicate things, increasing the workload for technologists, technicians and physicians, thus reducing productivity and hampering the patient experience. Moreover, inadequate hardware and software support can disturb laboratory work process prolonging the duration of results and interfering with the workflow [6]. Insufficient training and lack of knowledge on the system can interfere with efficient use of digital tools, ultimately preventing them from achieving the true potential for diagnostic accuracy and healthcare delivery [6, 9].

1.2 Background

1.2.A. Artificial intelligence

Artificial intelligence is a technology used in multiple sectors, including healthcare sector, to optimize processes and enhance organizational efficiency and support data-driven decision making [10, 11]. It is a

system that can think like a human cognitive function through intelligent agents that are able to analyze environment and execute specific tasks [10, 11, 12]. Usually, the AI system acquires data, processes and interprets patterns through algorithmic learning, and generates analytical or predictive outcomes [10, 11].

Learning in AI can occur through two approaches: supervised learning, where labelled training data is used to predict outcomes on new data set, and unsupervised learning, where patterns are identified without an earlier defined outcome [12, 13]. This learning mechanism is foundation of machine learning, a part of AI that enables systems to learn from data and improve performance with very little human intervention [12, 13].

Deep Learning (DL) is an advanced form of machine learning which uses multiple layers of artificial neural network to extract structured and complex features from large data sets [14, 15]. Another important domain is Natural Language Processing (NLP), module that enables computers to interpret, generate and analyze human language therefore facilitating the interpretation of unstructured data text into structured understandable language [16].

In clinical laboratory machine learning can analyze patient test results and flag abnormalities, predict disease progression, and automate workflow process [17]. In some areas deep learning modules can provide expert level performance and analyzing pathology slides or interpreting hematology images to detect abnormalities [17].

There are several deep Learning architectures widely used in clinical laboratory setups. Convolutional Neural Networks (CNN) are effective in analyzing image-based diagnostics such as blood smears for malarial parasites, classifying white blood cells and detecting cancerous cells in histopathology slides [18, 19]. Graph Neural Networks (GNNs) can provide models relationship showcasing patient laboratory parameters to identify disease patterns, predict outbreaks, and uncover association between biomarkers and clinical outcomes [20, 21]. Generative Adversarial Networks (GANs) enhances quality of images from low resolution equipment in environment with resource limitations and poor imaging equipment [22, 23]. Reinforcement Learning (RL) algorithms can optimize laboratory workflow managing testing schedule, resource allocation during high demand and prioritize urgent cases to reduce turnaround time [24].

Despite the advantages, there are certain limitations to implementations. Lack of proper integration of electronic records between patients and service providers restrict comprehensive data utilization and may compromise predictive accuracy [19]. Variation in staining protocols, clinical procedures and equipment can cause ‘dataset shift’ where models trained for a particular set of data perform poorly on data generated under different conditions [18, 19]. Additionally, for successful deployment of AI integrated systems requires a complex infrastructure, high-speed network, and standardized data framework [12, 13, 14]. These resources remain limited in many developing countries.

1.2.B Cloud Computing

Cloud computing is an on-demand delivery of computing service by cloud providers that includes server, storage, databases, networking, analysis, and integration with AI—over the internet by service providers such as Microsoft Azure, Amazon Web Services (AWS), and Google Cloud Platform [25, 26]. The service provided is rapid with minimal management efforts or service provider interaction enabling rapid innovation, operational flexibility and scalable resources utilization [25, 26]. Rather than investing in and maintaining physical data centers, health care sectors can access cloud based-infrastructure through pay–as–you–go pricing model, thereby reducing capital expenditure and improving cost efficiency [25, 26].

There are five essential characteristics of cloud technology. On-demand self-service which allows users to provision resources automatically without direct intervention with service providers [27, 28, 29]. In Clinical Laboratories, technicians/ technologists can request additional storage or processing power as needed. Broad network access ensures services are accessible over internet-based network allowing laboratory results to be securely retrieved from multiple departments. Resource pooling enables multiple hospitals to share cloud infrastructure securely [27, 28]. Rapid elasticity allows computing capacity to scale up or down based on laboratory workflow especially during peak testing periods [27, 28]. Measured service ensures resources consumption is monitored and billed according to usage, optimizing departmental expenditure [27, 28].

Cloud computing supports healthcare information system through service models such as Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS), which facilitates standardized deployment of electronic system with minimal hardware dependency [29]. Object storage architecture like cloud–based storage buckets are significant for clinical labs as it enables scalable management of unstructured data such as digital pathology or hematology slide images, reports, genomic files sequences [30].

Security components are integrated into cloud services. Identity and Access Management (IAM) regulates user permission, ensuring data accessed by authenticated personals (example, technologists have editing right, doctors with read read–only access, and researchers accessing anonymized datasets) [31]. Encryption protocols secure data in transit or rest, allowing decryption only by authorized personal [32]. Additionally, Security information and Event Management (SIEM) monitors security threats and detect anomalous patterns and potential cybersecurity threats [33].

Despite the advantages challenges exist. Reliable network strength and connectivity, technical expertise, and strong cybersecurity are pre-required for successful implementation [6]. A survey in 2025 found 96% of Health Organization who believed that existing security is insufficient to support large–scale AI deployment, which highlights the current concerns regarding data protection and system resilience [34].

1.3 Need/Gap Analysis in the Asian Subcontinent.

Though the AI-powered solutions are already present in the market, there are certain limitations to implementations. Lack of proper integration of electronic records between patients and service

providers restricts comprehensive data utilization and may compromise predictive accuracy [19]. Variation in staining protocols, clinical procedures, and equipment can cause ‘dataset shift’ where models trained for a particular set of data perform poorly on data generated under different conditions [18, 19]. Additionally, for successful deployment of AI-integrated systems requires a complex infrastructure, high-speed network, and standardized data framework [12, 13, 14]. These resources remain limited in many developing countries.

Similarly, those cloud service providers are there with advanced technology and fast services; challenges exist. Reliable network strength and connectivity, technical expertise, and strong cybersecurity are pre-required for successful implementation [6]. A survey in 2025 found 96% of health organizations believed that existing security is insufficient to support large-scale AI deployment, which highlights the current concerns regarding data protection and system resilience [34].

1.4 Objectives.

The objective of the study aims to it the existing method of data storage access and utilization- whether the electronic or paper-based within the laboratories of South Asian countries (Nepal, Bhutan, and India). To know the global transactions from paper-based systems to cloud based systems. The study also assesses the implementation barriers, and retrospective willingness to learn AI-based solutions by the technical workforce. The study highlights the need for proper infrastructures, and the need for training to streamline the adaptation of AI-based solutions. Seeing the expectation gap between current system and the desired system is also highlighted in this study.

Null Hypothesis (Ho)

There is no significant difference in efficiency or cause effectiveness between current story system and AI powered system in clinical laboratory.

Alternate Hypothesis (Ha)

An AI-Powered storage system results in more efficient and scalable solution to address the laboratory data moderated by implementation barriers such as staff willingness, training and device interoperability.

Methods and Materials

Study Design

The survey questions were selected and designed comprehensively to assess the current state of data management, infrastructure of digital facilities used, and readiness for the adoption of AI powered cloud storage system in clinical/ medical laboratories. The questions were selected form the retrospective survey done in European and Italian hospitals [1, 2]. The questions were structured into five categories for easy analysis. The survey was prepared in google survey form linked with google sheet. The features of the survey questionnaire used are provided in Table 1.

The categories of questions are as follows:

1. General Characteristics.

This section included an analysis of the professional and demographic profile of participants to make their responses more contextualized and identify variation across different groups.

2. Adequacy of Digital Instrumentation.

This set of questions analyzed and investigated existing IT infrastructure and how comfortable the participants are to use the infrastructure available. This can be also analyzed to find the readiness to adopt AI advanced cloud-based system.

3. Access to health data and issues of current system used.

This section highlights the challenges and ineffectiveness of current system (paper based or LIS or cloud-based) exploring the current data handling practices and user experience.

4. Laboratory data management and analysis.

This set of questions was designed to understand the tools (such as SPSS, SAS, Python, AQL, Google Cloud, AutoML, etc..) and processes used for data handling and perceive the adequacy of data analysis.

5. Perception and readiness for AI powered Solutions.

Last section of the survey used to collect data on participants familiarity with ai, expectations and concerns regarding AI- powered data management systems. It helped analyze human-born barriers for adoption of AI powered services and perceive information on willingness to learn and attend AI related workshops and training.

Study Population

In Bhutan and Nepal technologist working in various lab setup were asked to fill the form via link provided through WhatsApp, email, or passed on through friends. In India technologists and laboratory managers, doctors were surveyed through face-to-face interview or link were provided through QR scanner.

Sample Size

A total of 113 surveys were conducted from the three counties. As per inclusion criteria survey forms were passed on to only those technologists, technicians and physicians currently employed and dealing with the laboratory data, while being able to comprehend the survey and consenting to take the survey.

Table 1

Questions aligned with category & Area of Focus

Category	Area of Focus	Questions	Sub Questions
General Characteristics	Demographic, professional, and institutional context of participants.	1. Country you are currently working at (India, Bhutan or Nepal). 2. What kind of hospital or laboratory do you work in (Example Referral hospital, Specialty hospital, Private Lab, etc.). 3. Role in Laboratory? 4. Years of Experience. 5. How often do you work with patient data?	
Adequacy of Digital Instruments	IT infrastructure, hardware/software satisfaction, and cloud adoption.	1. Availability of corporate Wi-Fi and its adequacy. 2. Adequacy of software based on ease of use, maintenance required, integration with workflow, training requirement and overall satisfaction. 3. Adequacy of hardware based on ease of use, maintenance required, integration with workflow, training requirement and overall satisfaction. 4. Availability of cloud platforms and uses. 5. Type of cloud platform used.	
Access to health data and pain points of current system used, considering issues faced with paper-based system.	Challenges and inefficiencies in current data storage and retrieval.	1. Current practice of storing data (such as patient data, assigning tests, monitoring reagents, calibrations, and maintaining schedules, etc.) 2. How would you describe your experience with the paper-based data recording system?	1- very inefficient, 5- very efficient.

Category	Area of Focus	Questions	Sub Questions
		3. Challenges faced when using paper records. 4. Have you ever lost or misplaced important patient or lab data using the paper-based system? 5. Comfortableness of Electronic Laboratory Information System	
Laboratory data management and analysis.	Tools and processes for data analysis within the LIS.	1. Tools used in your lab for data analysis. 2. How easy is it to extract data from your Laboratory Information System (LIS)? 3.How do you rate the adequacy of data extraction in terms of speed and volume?	

Category	Area of Focus	Questions	Sub Questions
Perception and readiness for AI powered Solutions	Knowledge, benefits, barriers, and willingness to adopt AI solutions.	1. Are you familiar with computer-based or AI-based systems for data entry and storage? 2. Opinion on efficiency of switching to a computer or AI-based system 3. Opinion on benefits that AI/digital systems could provide in your lab work: 4. Perspective on what limits the use of AI in medicine nowadays 5. Level of knowledge about Artificial intelligence 6. Opinion on the following based on the rating of 1–5 where 1-strongly disagree and 5-strongly agree 7. Willingness to attend workshops on AI related topics.	1-very efficient, 5-very inefficient a. Faster data entry, easier access to records, b. improved accuracy, better data security, c. remote access to data, d. provides decision support for clinicians e. optimizes workflow. (Multiple answers can be selected a. Data privacy and security concerns b. lack of skills and difficulties for understanding too mathematical aspects c. development and maintenance are expensive d. especially for small or rural facilities e. legacy systems and fragmented workflows hinder smooth AI implementation f. standards for validation and accountability are still evolving g. lack of equipment (multiple answers can be selected) 1- bad, 5- excellent

Category	Area of Focus	Questions	Sub Questions
			a. I believe an AI-powered digital system could significantly improve data accessibility in the lab. b. I believe a digital system would make my daily data management tasks more efficient. c. I think an AI powered digital system would enhance the security of the lab data. d. I am willing to learn how to use a new AI-powered digital data management system. e. I am concerned that an AI powered system might be too complex to learn.

Data Analysis

Data analysis including statistics and creating tables was done using python (Jupyter Notebook platform was used). Chi square test was done to show association between Wi-Fi quality and software satisfaction. t-test was done to show significance between data loss using paper-based system and those who are not using the system anymore. t-test was also done to know the expectation gap between desired and current states of software.

Results

1.1 Demographic Profile of Respondents

A total of 113 participants from South Asian countries filled the survey. The response was distributed in the following manner, 38 (33.6%) participants responded from India and Nepal, and 37 (32.7) from Bhutan. (Table 2)

The participants were predominantly early-career and young. Largest age group was from 20–24 years (n = 37, 32.7%). Most common professional experience level ranged from less than a year to over 15

years (Table 2). In terms of professionalism, laboratory technicians and technologists were the most common professions with very few doctors responding to the survey. (Table 2)

Respondents were employed across various healthcare settings. The most common workplaces were in district and referral hospital, accounting for 22.1% and 20.4% of participants respectively. Followed by private laboratories (18.6%), specialty hospital (17.7%), and maternity hospital (11.5%). A smaller portion worked in regional hospitals (6.2%), charitable hospital (2.7%), and blood bank (0.9%). (Table 2)

Table 2
Demographic Profile of Respondents

Country	**Count**	**Percentage (%)**
India	38	34%
Nepal	38	34%
Bhutan	37	33%
Total	113	100%
Job Category	**Count**	**Percentage (%)**
Laboratory Technician	47	42%
Laboratory Technologist	40	35%
Laboratory Manager	11	10%
Laboratory In charge	6	5%
Students/Trainees	6	5%
Doctors	3	3%
Total	113	100%
Facility Type	**Count**	**Percentage (%)**
District Hospital	25	22%
Referral Hospital	23	20%
Specialty Hospital	21	19%
Private Laboratory	20	18%
Maternity Hospital	13	12%
Regional Hospital	7	6%
Charitable Hospital	3	3%
Blood Bank	1	1%
Total	113	100%
Age Group	**Count**	**Percentage (%)**
20–24 years	37	33%
25–29 years	34	30%
30–34 years	22	19%
35–39 years	13	12%

Country	Count	Percentage (%)
40–44 years	3	3%
45–49 years	4	4%
Total	113	100%
Experience Group	**Count**	**Percentage (%)**
< 1 year	23	20%
1–2 years	38	34%
3–4 years	21	19%
5–6 years	10	9%
7–9 years	14	12%
10-14years	3	3%
15 + years	4	4%
Total	113	100%

1.2 Adequacy of Digital Instruments

Availability of digital structure in Table 3 we can see corporate Wi-Fi was available in majority of laboratory facilities (95.6%), which shows white spread of access to network and connectivity. Cloud platform was available in 68.1% of facilities. Among which public cloud platforms were commonly used (76.1%), followed by private cloud (12.4%), while no response reported use of hybrid cloud system.

Adequacy of hardware and software systems were evaluated using linkage scale as shown in Table 4. Means course were comparable for both Software and Hardware across all parameters. Ease of use should identical mean scores for both hardware and software (3.88 ± 1.13 vs 3.88 ± 1.17; p = 1). Likewise, there was no statistically significant difference observed in maintenance (p = 0.817), integration with workflow (p = 0.787) or training requirements (p = 1). Overall satisfaction was slightly higher for software compared to hardware (3.80 ± 1.26) though statistical significance was not achieved.

Most of the respondents rated quality connection as fully adequate (47%) compared to software (41%) and hardware (40%). However, inadequacy ratings were also particularly notable in case of hardware and software system.

Moreover, analysis using Chi-square test (Table 5), demonstrated statistically significant association between Wi-Fi quality and software satisfaction ($\chi^2 = 89.778$, df = 9, $p < 0.001$). Additionally, comparison of distribution of connection quality and adequacy level across system showed statistically significant difference (p = 0.023).

Table 3
Availability of Digital Infrastructure

Parameter	Frequency (n)	Percentage (%)
Wi-Fi available	108	96%
Cloud platform available	77	68%
Public Cloud	86	76%
Private Cloud	14	12%

Table 4
Adequacy of Hardware and Software

Parameter	Software (Mean ± SD)	Hardware (Mean ± SD)	P-Value
Ease of Use	3.88 ± 1.17	3.88 ± 1.13	p = 1.000
Maintenance	3.92 ± 1.19	3.94 ± 1.14	p = 0.817
Integration	3.82 ± 1.14	3.81 ± 1.14	p = 0.787
Training	3.87 ± 1.20	3.87 ± 1.19	p = 1.000
Overall Satisfaction	3.80 ± 1.26	3.71 ± 1.28	p = 0.068

Table 5
Chi-Square Test for Association between Wi-Fi quality and software satisfaction

Statistical Measure	Value
Chi-square test Statistic	89.778
Degrees of freedom	9
P-value	p < 0.001
Sample Size	108

1.3 **Access to health data and pain points of current system used, considering issues faced with paper-based system.**

From the total respondents most participants (87.5%) reported using an Electronic Laboratory Information System (eLIS), while only 6.2% relied on paper-based methods and 6.2% used cloud base system indicating a strong preference for digital solutions (Fig. 1).

Among the paper base system users and those users with experience (n = 98) several challenges were identified. Most frequently reported issue was risk of physical damage or loss of record (32.8%),

followed by difficulty in retrieving information (25.6%), time consuming process (23.5%), and susceptibility to error (18.1%) (Table 7).

Comfort with electronic laboratory information system was high with a means score of 4.1 ± 0.957 on a 5-point scale. A significant portion of respondents 77.9% reported being comfortable (rating 4–5) while only 4.4% Express this comfort (rating 1–2), which indicates stronger user acceptance of electronic system (Table 6).

On contrast, paper-base system showed moderate satisfaction level with mean experience score of 3.07 ± 0.85. Only 23.5% of users reported satisfaction while 15.3% were satisfied and majority remained neutral (61.2%) (Table 7).

Data loss was a major concern among users, with 65.3% of paper-based users reporting instances of lost or misplaced data. The mean satisfaction score among users who experienced data loss was less (2.97 ± 0.82) compared to those who did not use it (3.3 ± 0.88). However, statistical analysis using independent t-test showed no significant difference between the groups (t= − 1.849, p = 0.0709) (Table 7).

Table 6
Comfort with eLIS

Parameter	**Count**
Mean ± SD	4.19 ± 0.97
Median	4
Range	1 to 5
Sample Size (n)	113
Comfortable User (Levels 4–5):	77.90%
Uncomfortable Users (Levels 1–2):	4.40%

Table 7
Experience with Paper-Based Data Storing Method & t-test Among Experience of Data Loss vs No Loss.

Parameter	Value
A. Sample Size	
Total Paper System Users (n)	98
Users With Valid Experience Rating	98
B. Paper-Based System Dissatisfaction	
Very Inefficient (rating 1)	6 (6.1%)
Inefficient (rating 2)	9 (9.2%)
Neutral (rating 3)	60 (61.2%)
Satisfied Users (rating 4–5)	23 (23.5%)
Mean Experience Score (1–5 scale)	3.07 ± 0.85
C. Data Loss Concerns	
Experienced Data Loss	64 (65.3%)
No Data Loss	27 (34.7%)
D. Dissatisfied Among Data Loss Group	
Users who experienced data loss	64 (65.3%)
Dissatisfied among data loss group (Ratings 1–2)	10 (15.6%)
Mean Score (Data Loss Group)	2.97 ± 0.82
Users with no data loss	27
Dissatisfied among no loss group (Ratings 1–2)	2 (7.4%)
Mean Score (No Data Loss Group)	3.33 ± 0.88
E. Statistical Comparison	
T-test (Experience: Loss vs No Loss)	t = -1.849, p = 0.709

1.4 Methods of laboratory data management and analysis adequacy.

Upon analysis spreadsheet (56.6%) was the most common tool used for data analysis, followed by Google Cloud AutoML (24.8%), and LabWare LIMS (19.5%). Advanced tools like python (15.9%), SPSS (11.5%), and SQL (8.8%) were less frequently used, suggesting a reliance on basic data handling methods (Table 8).

Looking into the ease of data extraction from Laboratory Information System, most respondents reported it is moderately easy (59.1%), while (22.7%) found it very easy and (18.2%) considered it complex. This suggested moderate usability but highlights existing challenge.

Looking at system performance, most of the participants rated LIS adequacy as moderate (65.5%) with only (7.1%) considering it highly adequate. While 27.4% rated the system as not adequate or slightly adequate. This indicates significant limitations in processing speed and volume handling by the system.

Table 8
Tools used for data extraction.

Rank	Tool	Count	Percentage (%)
1	Spreadsheet (Example, Excel)	64	56.60%
2	Google Cloud AutoML	28	24.80%
3	LabWare LIMS	22	19.50%
4	Python	18	15.90%
5	SPSS	13	11.50%
6	SQL	10	8.80%
7	SAS	5	4.40%
8	Others	1	0.90%

1.5 Perception and readiness for AI powered Solutions

Majority of the respondence reported being familiar with AI system (71.7%), while 19.5% of the respondents were partially familiar and only 8.8% reported no familiarity.

More than half of the respondents (53.1%) demonstrate it high level of AI knowledge. 30.1% of respondents reported moderate knowledge, while 16.8% had low knowledge. This finding shows that participants were familiar with AI and had knowledge on the matter.

Table 9 shows the persist benefits of AI. Most frequently mentioned benefits were faster a data entry (54.0%), better security (52.2%), and easier access (50.4%). Improved accuracy (49.6%) and remote access (47.8%) were also valued. Decision support (42.5%), and workflow optimization (32.7%) were less frequently mentioned but also noticeable.

As shown in Table 10 there are some barriers highlighted to AI adoption. It includes high cost and rural limitations, which were the most significant barrier with each reported by 57.5% of survey takers. Legacy system (44.2%) and data privacy concern (34.5%) also posed challenges. Skills shortage (30.1%), lack of standardization (27.4%) and lack of equipment (22.1%) were some additional obstacles that were noted. These findings suggest infrastructure and organizational factors hindering AI implementation.

Respondents rated willingness to learn highest (mean = 4.18, SD = 1.09), followed by accessibility (mean = 4.09, SD = 1.13) and efficiency (mean = 4.08, SD = 1.07). Security (mean = 3.95, SD = 1.14) and complexity concerns (mean = 3.93, SD = 1.31), were slightly less. Overall, perception was positive, with strong interest in learning and adoption.

Statistical testing (Table 11) shows noticeable expectation gap between current and desired states. Security showed the largest gap (Mean difference = 1.81, $p < 0.001$) with high improvement potential 79.8%. Accessibility showed a significant gap (Mean difference = 1.81, $p < 0.001$). Efficiency had a moderate gap (Mean difference = 0.92, $p < 0.001$). Ease of use however, showed negative gap (Mean difference= − 0.76, $p < 0.001$) indicating current system exceeded the desired expectation in this dimension. Overall satisfaction showed a significant gap as well (Mean difference = 0.32, $p = 0.0039$). This suggests accessibility and security are a critical area for improvement while ease of use is perceived as already exceeding expectations.

Table 9
Perceived benefits of AI

Benefits	**frequency (n)**	**Percentage (%)**
Faster data entry	61	54%
Better security	59	52%
Easier access	57	50%
Improved accuracy	56	50%
Remote access	54	48%
Decision support	48	43%
Workflow optimization	37	33%

Table 10
Perceived barriers to AI adoption.

Berries	**Frequency (n)**	**Percentage (%)**
High cost	65	58%
Rural limitation	65	58%
legacy system	50	44%
Data privacy	39	35%
Lack of skills	34	30%
Lack of standard	31	27%
Lack of equipment	25	22%

Table 11
Expectation gap between current system and desired software.

Dimensions	n	Current	Desired	Mean Difference	t-stat	p-value
Efficiency	113	3.38	4.3	0.92	-9.363	< 0.001
Accessibility	113	2.27	4.09	1.81	-16.714	< 0.001
Security	113	2.12	3.95	1.83	-9.695	< 0.001
Ease of Use	113	3.88	3.12	-0.76	6.435	< 0.001
Overall satisfaction	113	3.8	4.11	0.32	-2.948	0.0039

Discussion

The study provides important insights into current state of laboratory data management, digital infrastructure, and the readiness of medical laboratory for artificial intelligence (AI) adoption in developing South Asian countries (such as Nepal, Bhutan, and India). The adoption of electronic Laboratory Information System in the study has observed an ongoing global transaction towards digital healthcare systems [35], which supports better data handling and workflow efficiency. However, despite wide spread of digitalization, predominant use of paper-based system and spreadsheets for data management indicate limited utilization of advanced technology which suggest that full potential of available data is underutilized.

The moderate rating of ease of data extraction and system performance highlights the ongoing inefficiency with the existing Laboratory Information System. These findings remain consistent with previous studies where factors such as limited data accessibility, poor interoperability, and dependents on IT support significantly restrict effective data utilization [1, 2]. In most medical cases, laboratory data cannot be interpreted segregated and must be integrated with clinical information such as patient history, and treatment details which make data extraction and analysis more complex [1]. Furthermore, current LIS framework often fails to meet "Big Data" characteristics particularly in terms of capacity and speed, therefore it limits the suitability for AI–driven solutions [2].

Infrastructure-related challenges also were a critical barrier that emerged. Although most of the laboratories reported access to basic digital resources, limitations in hardware and software, cloud integration and Wi-Fi speed, reduce efficiency and scalability. Similar observations have also been reported in other studies, where poor infrastructure and restricted access to cloud-based platforms hindered the implementation of advanced technology [2]. Which provides key level storage and computational power is essential for AI integration however it's Limited adoption for the restricts system performance and innovation [36].

Despite the challenges, the study also shows a healthy attitude towards AI, it notes high level of awareness knowledge and willingness to learn among respondents. This also aligns with existing

literature showing a growing interest in AI across healthcare professionals [1, 2]. However, a significant gap remains between awareness and practical expertise, which largely occurs due to insufficient training opportunities or lack of specialized personal such as a data scientist [2]. The limited availability of pre-trained models for laboratory data, combined with complexity of interpreting result, further complicates AI Adoption in laboratory medicine [1].

The barriers to an implementation such as high cost, infrastructure limitation, data privacy concerns, and lack of standardization—suggests that challenges are multifactorial and not isolated [1, 2]. Addressing this issue will require coordinated efforts to improve IT infrastructure and enhance interoperability of LIS systems, increased investment in training and education, and stronger collaboration between every time professionals, data scientist, and technology providers.

Structure and Technology caps identified in this study must be flute in context of national healthcare investment across countries. Recent budget allocation indicates increasing commitment towards trending health care system. For instance, Nepal allocated approximately 716 million USD for Healthcare sector in the FY 2025/26 [37], while India located significantly higher amount of 12.7 billion USD [38]. Similarly, Bhutan allocated around 154 million USD towards healthcare development in same fiscal period [39]. This investment presents important opportunity to address existing limitations to laboratory infrastructure which will intern support the integration of advanced technology such as artificial intelligence. However, findings of the study suggest that financial investment alone may not be sufficient unless a backed by targeted strategies focusing on workforce training, system integration and data accessibility. Therefore, adjusting the national investment with digital health priorities and AI readiness will be essential to achieve high improvements in laboratory efficiency and healthcare outcomes.

Limitation

The study has certain limitations. Survey responses may be subject to reporting bias, and sample size and regional focus may limit generalizability. Moreover, laboratory settings and resources across countries may also inference that applicability of results. Additionally, methods of standardization for AI training-data (like standardized staining techniques) have not been discussed.

Conclusion

The study examines the current structure of laboratory data management and artificial readiness in Nepal India and Bhutan healthcare settings. While there is wide spread of electronic Laboratory Information System which demonstrates significant progress towards digitalization. Finding shows the ongoing challenges with data accessibility, system performance and advanced analytical capabilities. Continuing reliance on basic tools like spreadsheet along with moderate satisfaction in data extraction and systemic inadequacy suggest that the existing system is not yet efficient for AI integration.

Though there are limitations, there is a positive perception and growing interest in artificial intelligence among the laboratory workers. However, breaches like technical expertise, infrastructure, and

interoperability, along with financial and regulatory restrictions continue to disturb the effective implementation of AI based solutions. Fixing the issues is going to require multi-faceted approach which includes strengthening digital infrastructure, improving data integration and investing in work force training.

Digital transformation in laboratory is well underway, significant gaps remain in system performance, data accessibility, and advanced analytical capabilities. However, with strategic implementation and appropriate investments, AI has the potential to significantly enhance diagnostic accuracy, workflow efficiency and overall healthcare outcomes.

Declarations

Funding Declaration

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Approval Committee

The study was approved by Institutional Research committee of Symbiosis Institute of Health Sciences and Institutional Ethics Review Committee at Symbiosis International University.

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Figures

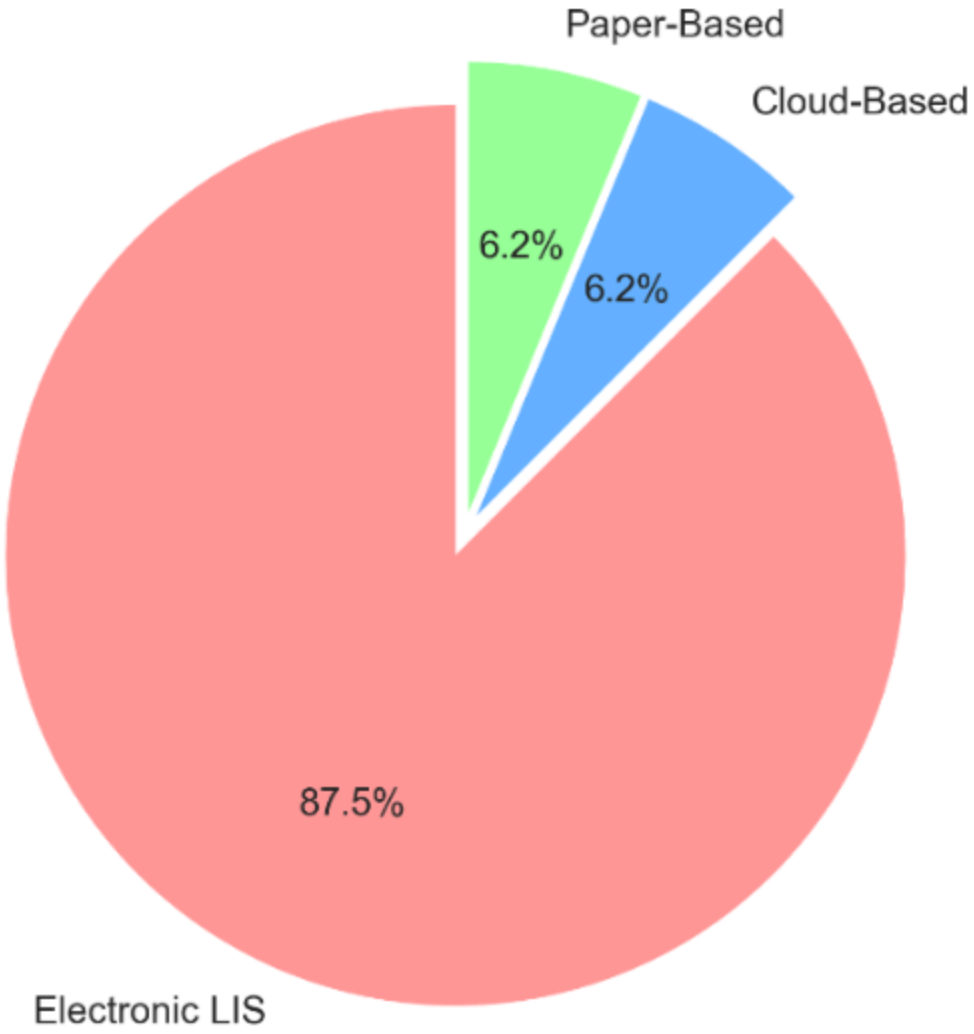


Figure 1

Distribution of data storage practice